Improving Post-Disaster Recovery:
Decision Support for Debris Disposal Operations

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ABSTRACT

Disaster debris cleanup operations are commonly organized into two phases. During the first phase, the objective is to clear debris from evacuation and other important pathways to ensure access to the disaster-affected area. Practically, Phase 1 activities largely consist of pushing fallen trees, vehicles, and other debris blocking streets and highways to the curb. These activities begin immediately once the disaster has passed, with the goal of completion usually within 24 to 72 hours. In Phase 2 of debris removal, which is the focus of this study, completion can take months or years. Activities in this phase include organizing and managing curbside debris collection, reduction, recycling, and disposal operations (FEMA 2007).

This dissertation research investigates methods for improving post-disaster debris cleanup operations—one of the most important and costly aspects of the least researched area of disaster operations management (Altay and Green 2006). The first objective is to identify the unique nature of the disaster debris cleanup problem and the important decisions faced by disaster debris coordinators. The second goal is to present three research projects that develop methods for assisting disaster management coordinators with debris cleanup operations. In the first project, which is the topic of Chapter 3, a facility location model is developed for addressing the problem of opening temporary disposal and storage reduction facilities, which are needed to ensure efficient and effective cleanup operations. In the second project, which is the topic of Chapter 4, a multiple objective mixed-integer linear programming model is developed to address the problem of assigning debris cleanup resources across the disaster-affected area at the onset of

debris cleanup operations. The third project and the focus of Chapter 5 addresses the problem of equitably controlling ongoing cleanup operations in real-time. A self-balancing CUSUM statistical process control chart is developed to assist disaster management coordinators with equitably allocating cleanup resources as information becomes available in real-time. All of the models in this dissertation are evaluated using data from debris cleanup operations in Chesapeake, Virginia, completed after Hurricane Isabel in 2003.

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Chapter 1

Introduction

As a result of the terror attacks of September 11, 2001 and the recent increase of natural disasters, there has been significant emphasis at all levels of government on emergency management of large-scale disasters and catastrophic events. In the event of a disaster, whether natural or man-made, all available resources are immediately focused on saving lives by rescuing and evacuating people from danger zones and by providing food, water, shelter, medical supplies and treatment to people in the affected areas. Once emergency responders are confident that there is no longer any danger to human lives, the focus turns towards recovery activities such as rebuilding and cleaning up areas and property destroyed or damaged from the disaster (FEMA 2006).

Depending on the category and nature of the disaster, recovery activities can be quite complex, require effective coordination between decision makers, and involve substantial resources and cost. More importantly, the failure of emergency and disaster management decision makers to successfully coordinate recovery activities can significantly increase the time and cost of restoring damaged communities and result in severe social, political, and economic turmoil (Roper 2008). For example, in the case of Hurricane Katrina, nearly five years have passed since the storm hit the Gulf coast in August 2005 and cleanup and recovery activities, which are estimated to cost over $150 billion, have still not yet been completed. The response and recovery activities in the case of Hurricane Katrina have unfortunately illuminated the consequences of poor emergency management (FEMA 2006). Officials drew criticism from politicians and citizens for poor planning and decision-making, slow response, and inequitable allocation of resources during preparation, response, and recovery activities (Luther 2008). The

degree of devastation caused by the storm, coupled with mismanagement and poor leadership, led to political and social unrest that continues today and delivered a nearly fatal blow to recovery efforts aimed at restoring the economic infrastructure of the area. Similar problems can be found in the planning, response, and recovery efforts of other disasters, including the recent earthquake in Haiti, which occurred in January 2010 and left nearly 200,000 dead and more than twenty times as many injured (Associated Press 2010).

1.1 Emergency and Disaster Management

Emergency management (EM) of disasters differs significantly from EM of routine or everyday emergencies. As Quarantelli (2001) details, disasters differ qualitatively and quantitatively from routine emergencies in the following ways:

1. Local organizations are immediately overwhelmed and must quickly relate to many other unfamiliar organizations responding to the disaster. In a disaster, huge numbers of existing public safety, government, medical, volunteer, charitable, and groups from other areas, newly formed groups, and private organizations all converge at the disaster area—a phenomenon that does not occur in routine emergencies often requiring response from one or only a few organizations.

2. Organizations lose independence and freedom as community disaster needs and values become more important than individual autonomy.

3. Largely because a disaster affects an enormously large number of people compared to a routine emergency, organizations become subject to different performance standards. Rather than seeking to respond with resources or medical treatment as quickly as is possible in the case of everyday emergencies, the objective in disaster management shifts

towards ensuring that resources and medical facilities are equitably distributed across the entire area and to the many victims of the disaster in the most timely manner.

4. Public and private organizations interact at a faster and closer level. For example, standard operating procedures and policies for requisitioning and bidding are often bypassed for the greater good in order to obtain needed resources.

In his recent book, Robert McEntyre (2007) distinguishes between accidents, crisis, disasters, and catastrophes based on amount of injuries, deaths, damage, disruption, resources and responders needed, and the time to recover. He suggests that accidents involve the fewest or least number, with crises, disasters, and catastrophes increasing in order across the eight characteristics.

While there is agreement in the literature of clear differences between routine emergencies and disasters or catastrophes, there seems to be no universally accepted terms distinguishing between these two types of crises. Often, the terms "emergency management" or "emergency response" are used when referring to both routine emergencies and disasters (Gendreau et al. 2001, Kolesar 1974, Larson et al. 2006). Likewise, the term "large-scale emergency" is sometimes added when referring to a disaster as defined by Quarantelli (2001) (Jia et al. 2007b, Larson 2005). Other terms, such as "no-notice disaster" and "high-consequence, low-probability (HCLP) event" have also been used to distinguish disasters from routine emergencies (Chiu and Zheng, 2007, Larson et al., 2006). For purposes of this research, the terms "disaster management" (DM) and "disaster operations management" (DOM) will be used to refer to the planning and operational activities related to a disaster as defined by Quarantelli (2001). The terms "emergency management" (EM), "management of daily or

routine emergencies," and "routine emergency management" will be used when specifically referring to the planning and operational activities related to daily or routine emergencies.

DM is concerned with all four phases of the disaster life-cycle: mitigation, preparedness, response, and recovery (Altay and Green 2006, FEMA 2006, Green and Kolesar 2004). These four phases do not necessarily always occur sequentially with fixed starting and ending phases, but rather are commonly depicted conceptually using a circular pattern as depicted in Figure 1-1.

Figure 1-1: Disaster Life-Cycle

As described by FEMA (2006), mitigation is concerned with measures designed to prevent disaster or to minimize the loss of life, injury, and destruction in the event one occurs. In addition to occurring within their own phase, mitigation activities are often implemented simultaneously as part of recovery phase reconstruction activities. Commonly, activities will overlap between phases. For example, preparedness activities will overlap with response and recovery activities and recovery activities will often begin during the latter stages of response activities.

In the preparedness phase, response and recovery plans are formulated for various disaster scenarios with the goal of preparing the community for most effectively responding to a

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disaster if one were to occur. For example, comprehensive evacuation, shelter location, and medical and food distribution plans for responding to disaster are formulated during the planning stage. Activities during the response phase are focused on evacuating people from the danger zone, mobilizing emergency equipment and personnel, distributing needed food, water, and shelter supplies, and providing medical supplies and treatment. Recovery phase activities, on the other hand, involve restoring major services, such as water, electric, and telephone, removing debris, and rebuilding infrastructure, such as highways, bridges, buildings and homes, destroyed during the disaster. Recovery activities can be quite complex, require effective coordination between decision makers, and involve a substantial number of resources and cost.

Within the area of disaster recovery, debris removal represents a major task requiring operational planning and control (FEMA 2007). By far, most published research related to using operations research and management science methods in EM has been focused on mitigation with response and preparedness following next in order. As Altay and Green (2006) point out in their recent survey of the literature, "the area in dire need for more research is, without question, disaster recovery. Only one article on recovery planning was published in main stream [operations research/management science] outlets [they] studied [using their classification rubric]." Other recent research surveys echo similar findings (Green and Kolesar 2004, Larson et al. 2006, Wright et al. 2006).

1.2 Statement of the Problem

"Hurricane Katrina produced unprecedented destruction, resulting in disaster
debris from vegetation and man-made structures. Before Katrina, the event that
left behind the greatest recorded amount of disaster-related debris in the United

States was Hurricane Andrew in 1992, which generated 43 million cubic yards (CY) of debris in Florida's Metro-Dade County. When the demolition of damaged property in the New Orleans metropolitan area [alone] is complete, Hurricane Katrina will have generated more than 100 million CY of disaster debris" -- *Congressional Research Service Report for Congress: Disaster Debris Removal After Hurricane Katrina: Status and Associated Issues, April 2, 2008*

One of the most important initial aspects of disaster recovery operations is the removal and disposal of debris from the disaster-affected area. Although the nature of debris or waste can vary depending on the type of disaster, disaster debris is often a mixture of all or most of the following: general household trash and personal belongings, construction and building materials, trees, vegetative and organic waste, hazardous waste, appliances, and electronic devices. Each of these categories of waste has its individual challenges for disposal even under normal conditions, and additional disaster-caused combinations of these categories often create new mixed categories with increased complexities for separating, cleaning, and disposing of the waste (Roper 2008).

Disposing of disaster debris can also be quite challenging because the amount of debris is usually extremely significant and is generated very quickly, in a matter of hours or minutes, depending on the type of disaster—far exceeding typical amounts of solid-waste generated on an annual basis. Also, in the case of large-scale disasters, debris is often spatially scattered throughout a large area encompassing several regions, counties, or states. Hurricane Katrina, which generated the greatest amount of hurricane debris ever recorded in history, deposited over 118 million cubic yards of debris over an area of 90,000 square miles, which included several

states (Hansen et al. 2005, Jadacki 2007). In Louisiana alone, the storm generated over 53 million cubic yards of curbside household debris as compared to 95,000 cubic yards generated annually as a result of normal conditions. These numbers are staggering considering that the amount of curbside household debris mentioned above does not include waste from demolition and construction or any other categories such as appliances, hazardous waste, or trees, shrubs, and other organic material, which can also be significant. The Army Corps of Engineers, for example, "removed 36 million pounds of rotten meat and other food [items] from several large commercial cold storage facilities from the New Orleans area" alone (Luther 2008).

Although the locations and amounts of debris can be easily summarized looking back after recovery activities have been completed, their overwhelming and immediate nature following the disaster make them very difficult to accurately determine or forecast in real-time as recovery operations begin and while they are ongoing (FEMA 2007). Disaster management coordinators (DMC) rely on debris inspection teams to initially survey the disaster area, which practically includes a "sweep" of important intersections and transportation routes. However, because the inspection teams are most always unable to cover or access the entire disaster-affected area and to make consistent and accurate debris estimates, this incomplete—or worse—inaccurate information can lead DMCs towards sub-optimal decisions and potentially make a bad situation even worse (Swan 2000a). Inaccurate estimates can result in inefficient allocation of resources, increased costs, prolonged recovery period, and increased social, political, and economic unrest (Roper 2008, Luther 2008).

An additional factor preventing inspection teams from accessing damaged areas is that, typically, a major portion of total debris often occurs on private property and is placed at the curbside by property owners for pick-up by public workers or contractors (FEMA 2007). This

process forces disaster management coordinators to rely on estimates from property owners who decide to call the disaster operations center to report debris for pick-up and on estimates based on daily disposal amounts, both of which provide uncertain, incomplete information regarding the entire situation. As a result of this uncertainty, DMCs are looking for effective ways to accurately estimate debris locations and quantities, prioritize damaged areas, and assign debris removal teams for cleanup (Luther 2008, McCreanor 1999, Roper 2008, Swan 2000b, Trimbath 2005).

The total cost of debris cleanup operations, which typically accounts for 27% of post-recovery costs, is significant and can severely impact local, state, and federal financial resources (FEMA 2006). In the case of Katrina, administrative debris cleanup costs alone were estimated to approach $330 million, accounting for over 8% of total debris disposal costs that have totaled more than $4.4 billion (Jadacki 2007). While a portion of debris cleanup is subsidized by federal agencies, primarily the Federal Emergency Management Agency (FEMA) and the Federal Highway Administration (FHWA) when a federal emergency has been declared, the majority of debris cleanup costs remain the responsibility of local and state governments. Spending too much on debris cleanup can strain financial resources, jeopardizing the success of rebuilding and restoration efforts.

The combination of these factors, along with an extreme sense of urgency to dispose of the debris as quickly as possible, creates challenges for emergency management personnel seeking to efficiently and equitably allocate resources—funds, personnel, equipment, landfill space, etc.—in support of response and recovery operations. On one hand, debris removal is critical for saving lives. As quickly as possible, rescue teams need clear pathways in order to reach and evacuate people from the danger zone and to deliver life-sustaining aid to people in

affected areas. On the other hand, debris removal is necessary for returning the physical, economic, and social infrastructure to pre-disaster conditions. As efficiently and equitably as possible, rebuilding teams need to cleanup damaged areas, restore life-sustaining infrastructure services such as water, sewer, electric, and telephone, and repair and rebuild structures damaged or destroyed from the disaster.

As a result, debris removal activities are commonly organized into two phases. During the first phase, the objective is to clear debris from evacuation and other important pathways. Preventing further damage to property, separating and disposing of debris and other considerations are secondary considerations in this phase. Practically, phase one activities largely consist of pushing fallen trees and debris blocking streets and highways to the curb and is generally completed in a relatively short period of time—usually within 24 to 72 hours. In phase 2 of debris removal, which can take months or longer, speed of debris removal remains an important consideration, but now additional objectives such as equitably allocating recovery resources, efficiently locating temporary separation and disposal facilities, maximizing recycling, and responsibly managing the overall costs of recovery become increasingly important (City of Chesapeake 2007, FEMA 2008).

Accurately estimating the locations and amounts of debris are critical to successfully allocating resources and assigning debris disposal teams for cleanup. Debris amounts can vary depending on the type and nature of a disaster. For example, Hurricanes Isabel in 2003 and Bonnie in 1998, both category 2 hurricanes accompanied with relatively low precipitation when they made landfall, generated over 1 million and 350,000 cubic yards of organic debris (trees, shrubs, etc.) respectively and very little construction and demolition debris. In contrast, Hurricane Floyd, also a category 2 when it made landfall, but accompanied with record

precipitation, generated very little vegetative debris, and more construction and demolition debris as a result of severe floods (City of Chesapeake 2007). Although hurricanes draw much attention in terms of debris, other types of disasters such as tornadoes, wildfires, earthquakes, volcanic eruptions, floods, etc. that affect large areas may include additional categories of debris and can also bring similar challenges. Looking back after all debris removal operations have been completed, the locations and amounts of debris cleaned up can be easily calculated. However, at the onset and while operations are ongoing, accurately estimating the locations and amounts of debris is one of the most difficult challenges for EM coordinators in search of effective methods for equitably allocating resources during debris cleanup operations (City of Chesapeake 2007, McEntyre 2007). Developing methods for equitably allocating debris cleanup resources considering the inherent uncertainty in post-disaster recovery is the focus of this dissertation research.

1.3 Research Objectives and Methodology

The purpose of this dissertation research is to address the resource allocation challenges faced by DMCs in the wake of a large-scale disaster as they plan for and coordinate post-disaster debris cleanup activities. In doing so, this research will focus on using mathematical programming and statistical process control (SPC) methodologies to assist DMCs decision makers with what we call the Disaster Debris Cleanup Problem (DDCP). The DDCP includes addressing the problems of locating temporary debris staging and reduction (TDSR) facilities, contracting and equitably allocating necessary resources, and coordinating debris cleanup and recovery operations. Although collection and disposal of debris is a major challenge to recovery

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in the wake of any disaster, this research is specifically concerned with collection and disposal of debris generated from a hurricane.

The first manuscript (Chapter 3) of this dissertation research develops a facility location model to assist DMCs with locating and opening TDSR facilities in such a way to best incorporate recycling activities into disposal operations. This study responds to a recent FEMA policy change that provides, for the first time, financial incentives for communities to recycle by allowing them to retain revenue from the sale of recycled disaster debris. In this study, the TDSR Disaster Location Problem (TDSR-DLP) is formulated in terms of the classic facility location problem (FLP), which has been widely studied in the literature (Araz et al. 2007, Barreto et al. 2007, Batta and Mannur 1990, Chan et al. 2008, Current and O'Kelly 1992, Jia et al. 2007b, Rajagopalan et al. 2008, Sherali and Carter 1991). Extensions to the classic FLP are proposed, in light of FEMA's new policy, to accommodate the unique assumptions, objectives, and constraints of the TDSR-DLP.

The main purpose of the second manuscript (Chapter 4) is to develop a multiple objective programming (MOP) model that assists DMCs with allocating resources for post-disaster debris cleanup operations. Our aim is to develop a model that could be used in allocating debris cleanup resources immediately following a disaster and during the planning stage. This paper presents a multiple objective mixed integer linear programming model for assisting decision makers in allocating resources in support of disaster debris cleanup operations. A weighted-Tchebycheff goal programming approach is proposed to incorporate the unique assumptions, objectives, and constraints of post-disaster debris cleanup.

The final manuscript (Chapter 5) of this research explores the use of prospective statistical process control methods (SPC) for controlling on-going debris cleanup operations. A

primary challenge for DM coordinators during recovery is to equitably allocate resources. In the DDCP, equitable means fairly allocating resources based on the amounts and locations of debris, rather than based on political or other influence, so that cleanup operations across regions are completed in approximately the same time. Unfortunately, the amounts and locations of debris are uncertain for nearly the duration of cleanup operations. The focus in this portion of research is on using prospective SPC methods to assist DMCs with equitably allocating resources by detecting emerging debris patterns in real-time as debris information becomes available during cleanup activities.

The SPC methodology, which is of particular interest to our research study here, is the self-starting cumulative sum (CUSUM) control chart, which compares the accumulated deviations of on-going sample measurements from an expected in-control value estimated from the on-going process itself (Hawkins and Olwell 1998). If the accumulated deviation falls outside an acceptable interval, an alarm is triggered, and the process is said to be out-of-control. CUSUM SPC methods have been successfully used for prospective analysis such as Rogerson's method, which detected the onset of the Burkitt's lymphoma in Uganda (Chang et al. 2008, Rogerson 1997). Prospective SPC methods offer potential for assisting DMCs in allocating resources and controlling cleanup operations using emerging debris information.

All of the proposed models in this research are tested using real-world data from debris cleanup operations completed in Chesapeake, Virginia, after Hurricane Isabel, which made landfall in September 2003. The data were obtained from the City of Chesapeake Public Works Department, which was responsible for cleanup operations (City of Chesapeake 2004).

1.4 Contributions of the Research

This research investigates unique aspects of disaster debris disposal and quantitative approaches for solving the DDCP, which has not been previously explored quantitatively in the literature. Specifically, this dissertation contributes to the literature for improving post-disaster recovery phase activities by

- identifying the unique nature of disaster debris cleanup as compared to everyday solid-waste disposal motivating the need for additional research.

- developing a facility location model that incorporates new FEMA recycling policy incentives, assists DMCs with opening and locating TDSRs, and demonstrates the benefits of considering primary and alternate debris area assignment *a priori*.

- developing a multiple objective programming model for contractor assignment and demonstrating its potential for improving disaster debris cleanup operations.

- developing a self-balancing CUSUM statistical process control chart approach for assisting DMCs with ongoing debris cleanup operations and demonstrating its effectiveness for equitably allocating resources in real-time.

1.5 Organizational Outline

This first chapter provides an introduction and overview into the general nature of disaster and its distinguishing characteristics from everyday or routine emergencies. It also serves as an introduction to disaster management and the role that post-disaster recovery phase activities play within the disaster life cycle. The need for post-disaster recovery-related research and the importance of debris disposal to successful recovery was illuminated. Finally, the objectives of this dissertation research were summarized.

Chapter 2 is a brief literature review of emergency and disaster management, disaster debris disposal, facility location, multiple objective programming, and statistical process control as related to solving DDCP. Chapter 3 develops a facility location model for locating TDSRs and incorporating recycling activities into post-disaster debris cleanup. Chapter 4 develops a weighted-Tchebycheff goal programming model that incorporates multiple objectives for assigning contractors to debris areas. Chapter 5 uses prospective statistical process control methods to develop a self-balancing CUSUM chart for equitably allocating resources in real-time during ongoing cleanup operations. Chapter 6 offers a summary and conclusions.

Chapter 2

Literature Review

Although each manuscript (Chapters 3, 4, and 5) of this dissertation contains its own individual literature review, a brief review of emergency and disaster management, disaster debris disposal, facility location, multiple objective programming, and statistical process control as related to solving the DDCP is provided here.

2.1 Emergency and Disaster Management

Early work relating to emergencies focused on developing location coverage models for optimal assignment of emergency vehicles and facilities (Kolesar 1974, Green and Kolesar 2004, Kolesar 1973, Larson 1972). Green and Kolesar (2004) provide an excellent historical summary of the foundational work of Kolesar (1974) and Larson (1972) that grew out of projects for improving operations and responsiveness of the Fire Department of New York (FDNY) and the New York Police Department (NYPD) respectively and the location coverage models that evolved from their work. For example, over the years, their initial models have been extended to consider dynamic redeployment (Gendreau et al. 2001, Kolesar 1974), multiple time periods (Rajagopalan et al. 2008), hierarchical services (Daskin and Stern 1981), multiple response units (Batta and Mannur 1990), and districting requirements (Muyldermans et al. 2002).

Quarantelli (2001) contrasts everyday emergencies, such as the emergencies that were the focus of Kolesar's (1974) and Larson's (1972) works, with disasters by illuminating the differences in how they affect organizations. As Quarantelli (2001) points out, disasters, unlike everyday emergencies, require organizations to "relate to more and unfamiliar groups, [to forfeit or relinquish] autonomy, [to] change their performance standards, and [to] interact more closely

with other public and private organizations." He further distinguishes between disasters and catastrophes suggesting that catastrophes result in damage or destruction to nearly all buildings and structures and in reduced or complete inability of local government to function. While aspects of emergency research may be beneficial in disaster and catastrophe scenarios, these inherent differences suggest the need for closer examination and new research into the unique challenges of disaster management.

While considerable research has focused on daily or routine emergencies over the years, there is growing interest over the past decade in OR/MS research specifically focused on investigating the unique issues and problems related to disasters. In fact, the number of published journal articles in OR/MS publications has more than doubled from its pre-1990 level; however, this output has "not produced a critical mass of research when compared to other popular [OR/MS] topics such as supply chain management" (Altay and Green 2006).

Of the four phases of disaster management (mitigation, preparedness, response, and recovery), mitigation has received the most research attention. Iuchi and Esnard (2008) used three case studies to investigate mitigation and low-income community risk resulting from an earthquake or volcanic eruption and the community's resources available to minimize risk. Other qualitative studies focus on mitigation strategies for improving sustainability and decreasing environmental impacts (Khan 2008). Quantitative studies focused on mitigation activities have commonly used simulation and math programming methodologies. For example, in a recent study, simulation was used to develop a decision support system for debris-flow mitigation (Wei et al. 2008) and Markov decision processes were used in combination with simulation to examine hurricane damage vulnerability resulting from building code changes (Davidson et al. 2003).

Simulation and math programming have also been widely used in preparedness phase activities. Numerous planning models have been developed for evacuation (Bakuli and Smith 1996, Regnier 2008, Sherali and Carter 1991, Silva 2001) and distribution of medical supplies (Chiu and Zheng 2007, Lee et al. 2006, Yi and Ozdamar 2007). Research has also focused on forecasting such as predicting hurricane paths (Regnier 2008), spread of wildfires (Cheng and Wang 2008, Webb and Balice 2004), and estimating potential disaster-specific damage and destruction (Boswell et al. 1999, Cret et al. 1993, Santos-Hernandez et al. 2008, Simpson 2006).

The recovery phase has received the least attention in the literature (Altay and Green 2006). Although much of the research into recovery is qualitative in nature, Brown and Vassalou (1993) use math programming in formulating a mixed-integer programming model to assign teams to repair and rebuilding tasks following an earthquake.

2.2 Disaster Debris Disposal

The nature and importance of debris cleanup to the success of recovery operations has primarily been discussed qualitatively in the relatively few articles published in the academic literature. For example, Roper (2008) discussed the challenges involving debris cleanup following Hurricane Katrina and the need for increased recycling efforts. Dubey et al. (2007) discussed the disposal problems associated with large amount of arsenic treated wood in the debris. In one of the few quantitative studies, Wei et al. (2008) propose a decision support system for estimating debris flow resulting from a flood. The proposed DSS is discussed in terms of its use for estimating debris flows, evacuation planning, and mitigation activities. Many popular press, industry journals, and government documents have published articles discussing debris cleanup related to specific disasters (Hansen et al. 2005, Luther 2008, Ragsdale 2004, Stephenson 2008,

Trimbath 2005), the need for debris planning and management (City of Chesapeake 2007, EPA 2008, FEMA 2007, Goldstein 2005, Hall 2000, Jadacki 2007, Jerome 2005, McCreanor 1999, Swan 2000b), and the general nature of disaster debris (Bonnie 1998, Emerson 2003, Farrell 1999, Rhodes 2008, Swan 2000a, Thorneloe et al. 2007, Yepsen 2008).

Relatively few articles specifically studying debris disposal have been published in the academic literature. The primary focus of debris research has been on forecasting with recent interest in sustainability and recycling issues. Forecasting debris is important to successfully managing debris removal operations and requires different assumptions depending on the nature of the disaster. Subsequently, several studies proposed quantitative models for forecasting disaster generated debris for different categories of catastrophic events. For example, a debris forecasting model for a flood event and a framework for forecasting debris flows in the wake of a landslide and flooding have recently been published in the literature (Paudel et al. 2003). FEMA (2007) published the most widely used guidelines for estimating debris depending on the category of hurricane. We are unaware of quantitative research studies, such as we propose here, developing models for assisting DMCs with strategic or operational aspects of disaster debris disposal operations.

2.3 Facility Location

Facility location has been the focus of much research for nearly a century since it was introduced by Alfred Weber as the problem of locating a warehouse (facility) in order to minimize a weighted-distance from customers (demand)—what has become the well-known "Weber Problem (Brandeau and Chui 1989, Drezner 1992, Drezner 1999, ReVelle et al. 2008)." In general, the objective of the facility location problem is to locate one or more "facilities" among

a collection of possible, spatially-distributed locations in order to satisfy some objective with respect to "demand," which has evolved to include cost, time, and other factors in addition to distance.

Although still used in determining locations for warehouses and manufacturing facilities, facility location has also been used in many diverse applications adding broad meaning of the notion of "facility." The use of facility location models for locating ambulances, fire stations, taxicab fleets, helicopter landing areas, radio signaling towers, nuclear power plants, and health centers are among the many articles in the literature (Daskin and Stern 1981, Lee et al. 2006, Pirkul and Schilling 1988, Saadatseresht et al. 2009, Taylor et al. 1985). Several summaries of location research have been published over the years and interested readers are directed to Brandeau and Chiu (1989), Klose and Drexl (2005), Revelle et al. (2008), and Hamacher and Nickel (1998).

Facility location models can be broadly categorized, on one hand, as either discrete, continuous, or network models depending on the decision space for demands and locating facilities, which is especially useful and most common for organizing and identifying possible solution methodologies. In the continuous case, facilities can be located anywhere in the decision space, as contrasted with the discrete case, which chooses from a discrete set of possible locations. Both continuous and discrete location models assume that demands occur at discrete locations, while network models assume demands occur on a collection of connected nodes (Brandeau and Chui 1989, ReVelle et al. 2008, Sahin and Sural 2007).

Location models can also be broadly categorized, on the other hand, in terms of their objective function—whether to minimize the average distance between demand points and facilities (P-median model), minimize the maximum distance between any demand point and

facility (P-center model), or locate facilities within some specified distance from demand points (Location Set Covering and Maximal Covering Location Models). Objective-based classification is helpful in classifying, evaluating, and formulating appropriate models for specific application domains and problems (Hamacher and Nickel 1998).

2.4 Multiple Objective Programming

Multiple objective programming (MOP) methods have been the focus of extensive study in the literature for quite some time. The majority of multiple objective research studies have focused on multiple objective linear programming (MOLP) methods for solving problems involving continuous variables with objectives and constraints expressed as linear functions (Alves and Climaco 2001). Fewer studies, including those of Rassmussen (1986), Tamiz et al. (1999), and Hallefjord and Jornsten (1988), have focused on multiple objective integer linear programming (MOILP) methods for solving problems with integer restrictions on variables (many of these studies specifically study problems having only binary restrictions). Finally, Alves and Climico (2001) is one of few studies focused specifically on exploring aspects of multiple objective mixed-integer programming (MOMILP) methods for solving problems containing both continuous and integer variables. As they point out, while MOILP and MOMILP are closely related, techniques used in MOILP do not always directly transfer to MOMILP.

In general, MOP methods, also referred to as multiple objective optimization (MOO) methods, are commonly grouped into categories depending on the manner in which a DM specifies or articulates his or her preferences with respect to the objectives or goals of the problem. MOP methods are generally classified as prior articulation methods, progressive articulation methods, and posteriori articulation methods (Korhonen 1992).

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In prior articulation methods, as Korhonen (1992) and others have described, the DM specifies or makes trade-offs between objectives before model solutions are generated. In other words, the DM preferences are included in the model *a priori*. The most well-known prior articulation method and the most widely used MOP technique is goal programming (GP) (White 1990). The major criticism of goal programming and prior articulation methods in general is the difficulty involved in obtaining accurate preferences from the DM. Generally, DMs are asked to rank order or assign weights to objectives in such a way as to indicate their relative importance. While accurately assigning weights or preferences for two or three objectives may be viable in some situations, as the number of objectives increases the task can become nearly impossible (Hwang 1980). As a result, many researchers have proposed methods for assigning weights. For example, Hwang and Yoon (1995) proposed simply ranking objectives and then assigning weights in consistent increments to reflect the relative importance of each objective.

In progressive articulation methods, rather than require preferences *a priori*, the DM is presented with a set of possible solutions and asked to provide preferences relating to that particular solution set (Korhonen 1992). Using the DM response, a new solution set is generated and presented to the DM and this interactive process progresses until a preferred solution is obtained. Examples of progressive methods include the STEM, Zionts-Wallenius, and Interactive Tchebycheff methods (Steuer 1989). While progressive methods do not require DM preferences *a priori*, they require much more effort on the part of the DM to participate in the cyclical process and ultimately still depend on the DM's ability to provide accurate preferences to each individual solution set. Providing accurate preferences even when known solutions are available can still be a very difficult endeavor.

In addition to requiring more endurance and time on the part of the DM to cycle through the interactive process, progressive methods are more computationally complex and require more time to generate solutions especially as the size of the problem increases. The addition of integer variables in the problem also increases complexity and solution time. As a result, a major concern is the possibility that a DM may become dissatisfied with the process and abandon it before a preferred solution is generated (Marler and Aroro 2004, Korhonen 1992).

Posteriori articulation methods do not require any assessment from the DM before or during the solution process. As Hwang et al. (1980) and others describe, posteriori methods generate a complete or representative set of solutions from which the DM chooses the one which is preferred. While this process seems beneficial in that no information regarding a DM preferences or utility function is required, the challenge of determining the most satisfactory solution remains. The problem here results from the usually large number of possible solutions that are presented to the DM, which practically make it extremely difficult to accurately make trade-offs in the quest to choose the most preferred solution. Furthermore, generating large sets of solutions can be an extremely complex and time consuming process as computational demands again only increase when integer constraints are added and as the problem size grows (Hwang et al. 1980).

While MOLP methods differ in their underlying philosophy for specifying a DM's preferences or utility function, they also differ in their ability for generating optimal solutions (Hwang et al. 1980, Steuer 1989). An important aspect of quantitative multiple objective decision analysis is the ability of a solution method or approach to generate Pareto-optimal, efficient solutions, which is also of practical importance and assurance to DMs.

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<u>Optimality in Single-Objective Linear Programming</u>

In single-objective linear programming (LP), when a solution is optimal, a DM can be certain that no other feasible solution results in a better (higher if maximizing, lower if minimizing) objective function value. Figure 2-1 below shows the decision space for a hypothetical, single-objective LP problem with two decision variables, X_1 and X_2.
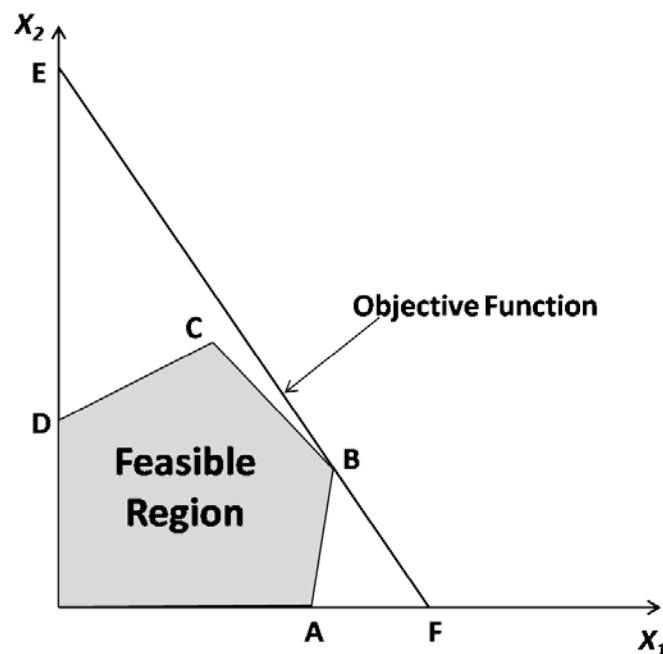
Figure 2-1: Optimality in Single-Objective LP

In a single-objective LP problem, the optimal solution point (determined by the objective function) will usually be an extreme or corner point of the feasible region, such as point B for the example in figure 2-1 (Ragsdale 2004). Changes in the objective function can lead to a different optimal solution. For example, in figure 2-2 below, a new objective function leads to a new optimal solution at corner point C.
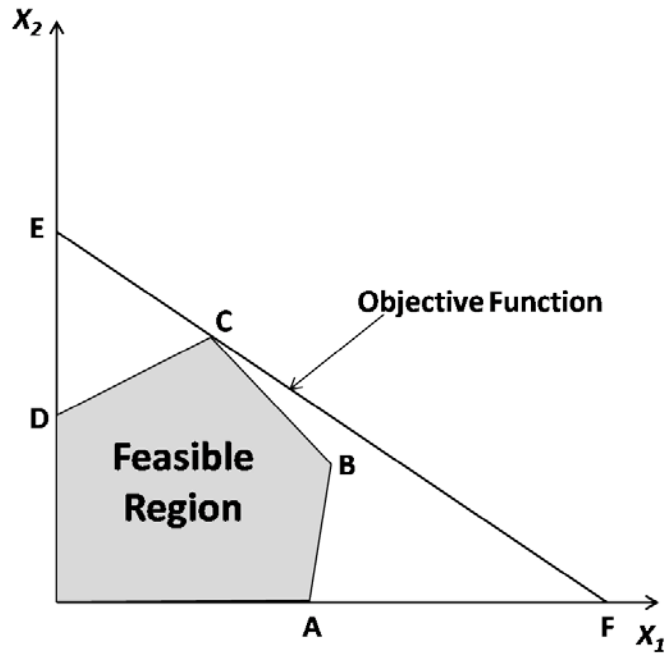
Figure 2-2: Optimality in Single-Objective LP

If the slope of the objective function is equal to the slope of the line segment BC, alternate-optimal solutions exist. In figure 2-3 below, the set of all alternate-optimal points is identified by the points forming the line segment from B to C (including individual points B and C).
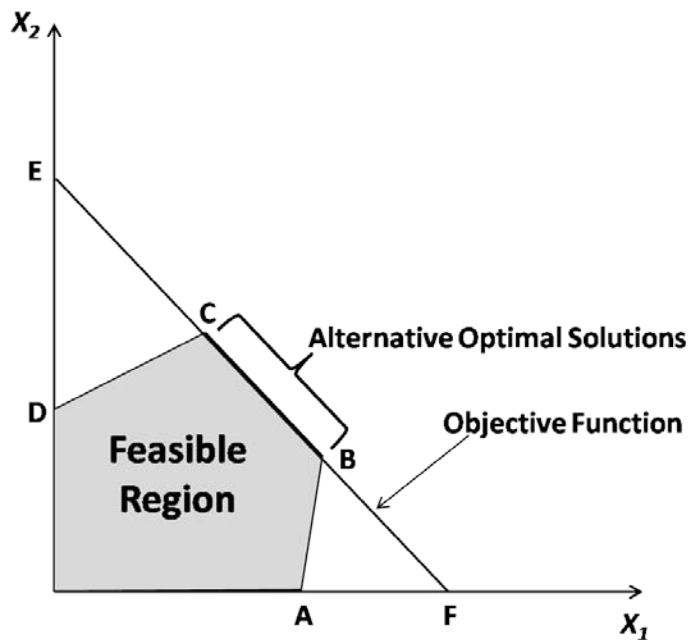
Figure 2-3: Alternative-Optimal Solutions in Single-Objective LP

Each optimal point on BC results in the same objective function value for differing values of the decision variables X_1 and X_2. Note that in the two variable case as shown in Figure 2-3, any move from an optimal point on line segment BC to any other optimal point that results in an increase to X_1 requires decreasing the other decision variable X_2. Likewise, any move from an optimal point on line segment BC to any other feasible point that results in an increase to X_2 requires decreasing the other decision variable X_1.

While the concept of optimality may appear straightforward enough in the single-objective LP case, in the presence of multiple objectives it becomes more complex as DM objective preferences are considered and solutions are represented by vectors rather than a single point.

Pareto-optimality in Multiple Objective Linear Programming

In MOLP, a solution for which one objective value cannot be increased (improved) without decreasing (worsening) the value of at least one other objective is called a Pareto-optimal, efficient, or non-dominated solution (Steuer 1989). The idea of non-dominance in MOLP may be visualized in the hypothetical case with two objectives, Z_1 and Z_2, as shown in Figures 2-4 and 2-5 below.
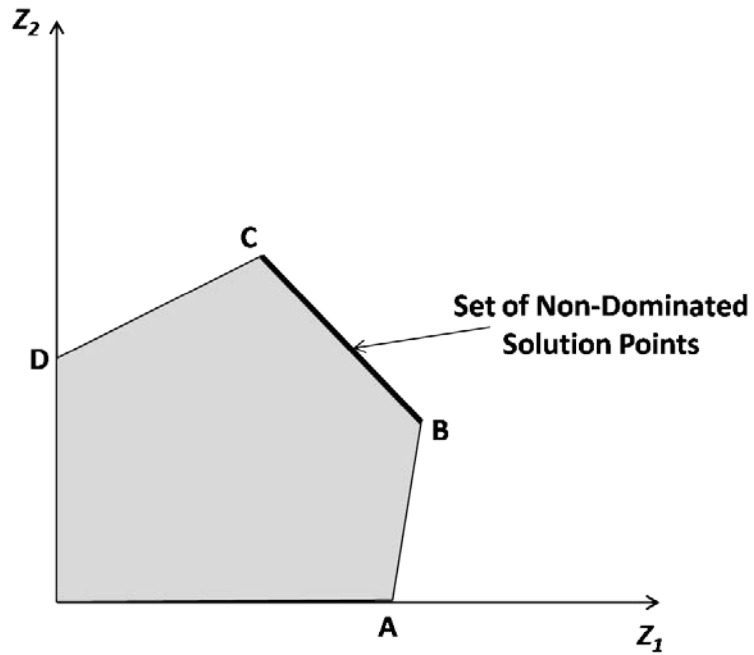
Figure 2-4: Pareto-optimality in MOLP with Two Objectives
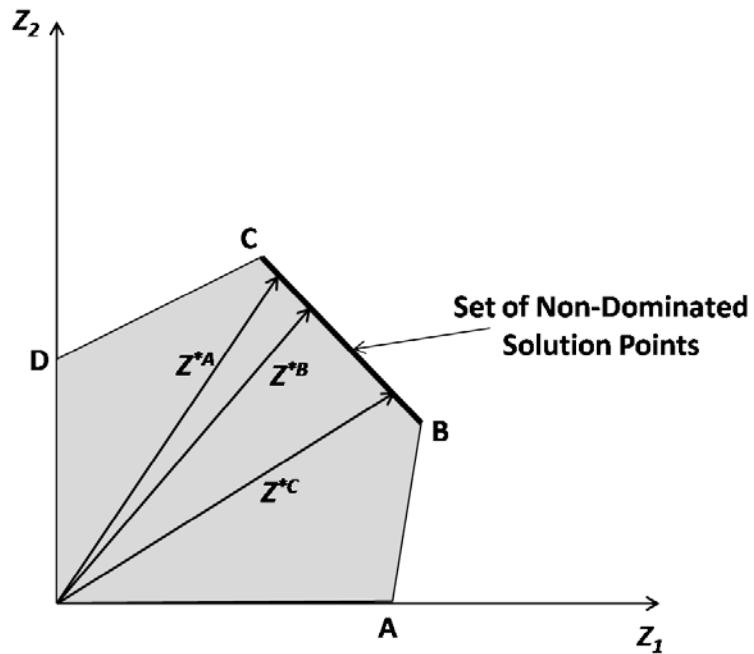
Figure 2-5: Non-dominated Solutions in MOLP with Two Objectives

In Figure 2-4, a move in any direction from any non-dominated solution point on line segment BC to any other feasible solution that results in an increase to Z_1, requires decreasing Z_2 (such as

shown in figure 2-5 when moving from Z^{*A} to Z^{*B}). Likewise, a move in any direction from any solution point on line segment BC to any other feasible solution that results in an increase to Z_2, requires decreasing Z_1 (such as shown in figure 2-5 when moving from Z^{*C} to Z^{*B}). The solution points on line segment CD (excluding the single point C) are not non-dominated solutions because in order to move from any point on CD (Excluding the single point C) to any other feasible point that results in an increase to the value of one objective requires that the value of the other objective also be increased. In turn, the points on line segment CD (excluding the single point C) are called *inefficient* or dominated solutions (Steuer 1989).

Specifically in MOLP, a solution vector Z^*, also called criterion vector Z^*, is called a non-dominated solution if it is not dominated by any other criterion vector Z. A criterion vector Z^* dominates another vector Z if at least one of its components is better than the corresponding component in Z and all of its remaining components are at least as good as the corresponding components in Z. A non-dominated solution in the decision space is called an efficient solution. The three terms—optimal, non-dominated, and efficient—convey the same meaning and are used interchangeably.

It is also important to consider the aspect of convexity because of its impact on solution methodologies. The points contained in ABCD, in Figures 2-4 and 2-5 above, form the set of all feasible solutions (feasible region), which is obviously convex in the case of linear objective functions and linear constraints as shown here. Significantly, a MOLP can be solved with standard LP software, such as Solver, which is included in Microsoft Excel (Steuer 1989).

<u>Pareto-optimality in Multiple Objective Integer and Mixed-Integer Linear Programming</u>

Unfortunately, as in the case of the DDCP, many real-world problems require that all or some decision variables be restricted to integer, often binary, variables. Examples include selection of forest management (Nhantumbo et al. 2001), telecommunications pricing (Brown and Norgaard 1992), nurse scheduling (Trivedi 1981), and water management (Hamalainen and Mantysaari 2001).

When one or more decision variable is restricted to integer and one or more continuous variables exist, the problem becomes a MOMILP whose solution space is also non-convex (problems with integer restrictions on all variables are called Multiple objective integer linear programming problems (MOILP)) (Alves and Climaco 2001). As a result of integer restrictions, the idea of non-dominance becomes more complex, and the ability to fully enumerate the set of all non-dominated points using MOLP solution methods becomes more difficult (Tamiz et al. 1999). Consider the hypothetical two objective MOMILP criterion space *Z* formed by the line segments AB and CD, which is obviously non-convex, as shown below in Figures 2-6 and 2-7 below.
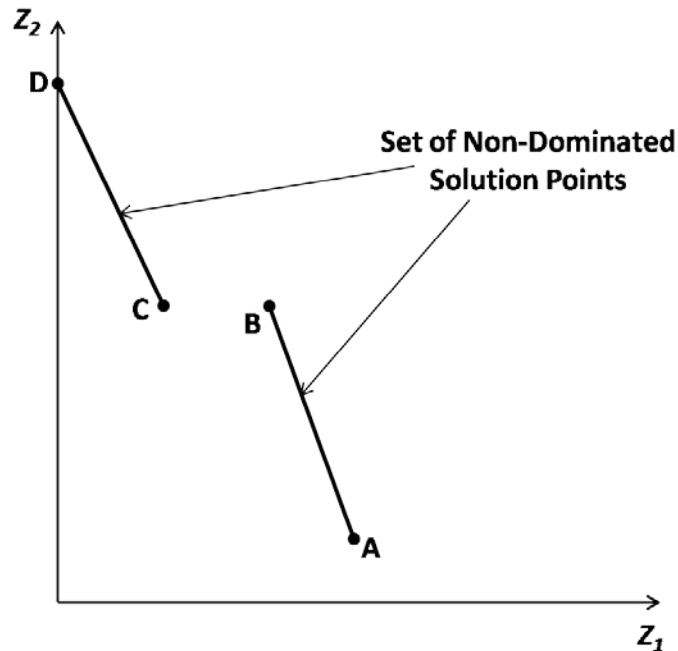
Figure 2-6: Supported Non-dominated Solutions in MOMILP with Two Objectives

The line segment AB and the line segment CD together represent the set of non-dominated solutions. The non-convex nature resulting from the integer restriction in MOMILPs leads to the need to further distinguish between *supported* and *unsupported* non-dominated solutions. A non-dominated solution is said to be unsupported if it is dominated by a convex combination, which does not belong to Z, of other non-dominated points belonging to Z (Alves and Climaco 2001). If a non-dominated solution is not an unsupported non-dominated solution, it is called a supported non-dominated solution.

In Figure 2-6 above, points on line segment AB are supported non-dominated solutions. However, the non-dominated points comprising the solution set CD, with the exception of the single point D, are unsupported non-dominated solutions because they are dominated by the convex combinations of points B and D as shown in Figure 2-7 below.
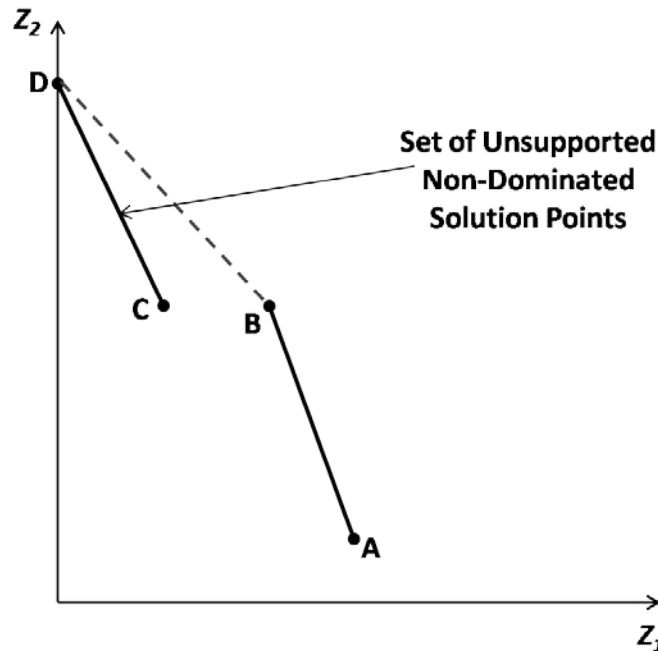
Figure 2-7: Unsupported Non-dominated Solutions in MOMILP with Two Objectives

The importance of whether a non-dominated solution is supported or unsupported has to do with the ability of generating both types of solutions, which together form the set of all non-dominated solutions. As possible in MOLP, unsupported non-dominated solutions of MOMILPs cannot be fully enumerated by parameterizing on weighted objective preferences using common MOLP formulations, such as a weighted-sums approach, with integer restrictions. (Alves and Climaco 2001).

As a result, a number of approaches have been suggested in the literature for fully generating the set of non-dominated solutions in MOMILPs. Most of the proposed methods that have been developed use progressive or interactive articulation of DM preferences (although prior or posteriori articulation may also be possible). Examples of these methods include STEM, GDF, the Visual Interactive Approach, and the augmented weighted Tchebycheff method, which is rooted in the properties of the weighted Tchebycheff metric (Steuer 1989).

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MINMAX Goal Programming

Goal programming (GP) is one of the most popular approaches for modeling problems with multiple objectives. Since its introduction nearly 50 years ago, several reviews and criticisms have been published including those by Ignizio (1978), Hannan (1985), and Aouni and Kettani (2001). In addition to the two main GP methods, the weighted-sum and lexicographic methods, additional extensions and approaches have been proposed.

Of interest to our research here is the MINMAX GP formulation, which is derived from the weighted Tchebycheff metric. In general, the MINMAX -GP seeks to minimize the maximum weighted deviation of each individual objective from its optimal target value, which is practically determined by solving for each individual objective. This optimal target value is also called the "ideal" or "utopian" value and is represented as point U in Figures 2-6 and 2-7 (Steuer 1989).

In the weighted Tchebycheff MINMAX GP approach, which can be use in the MOLP, MOILP, and MOMILP (and in non-linear cases as well), a DM specifies his or her preference for each objective *a priori* by assigning each one a weight (Tamiz et al. 1998). The Tchebycheff metric leads to a contour that defines the non-dominated solution for a particular set of weights as shown below for a hypothetical MOLP case and MOMILP case in Figures 2-8 and 2-9 respectively.
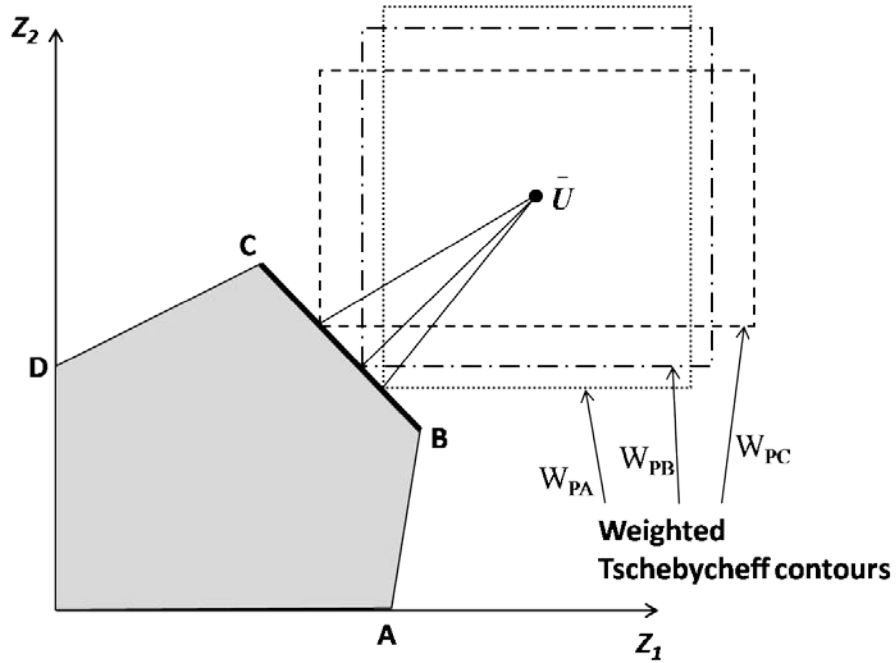
Figure 2-8: Weighted-Tchebycheff MOLP with Two Objectives
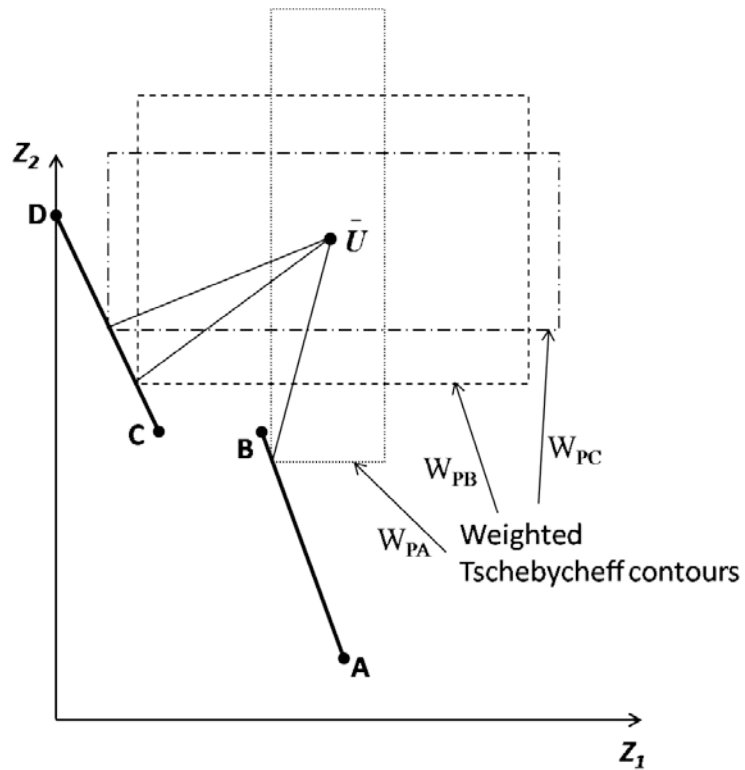
Figure 2-9: Weighted-Tchebycheff MOMILP with Two Objectives

By changing the weights or preferences (and resolving the problem), a DM can effectively

change the shape of the contour and generate the non-dominated solution that best satisfies those

preferences. In the figures above, each contour, W_{PA}, W_{PB}, and W_{PC}, defines one problem

solution that best satisfies a specified set of weighted objectives. Bowman (1976) proved that

the fully enumerated non-dominated solution set is generated by parameterization on the weights

in both linear and mixed-integer programs. It is well-known, however, that the weighted-

Tchebycheff approach may yield weakly non-dominated solutions (which are also unsupported),

such as point C (which is dominated by point B) in Figure 2-9 and several researchers, including

Steuer and Choo (1983), have developed progressive and posteriori methods for ensuring that no

weakly non-dominated solutions are generated.

While these methods may offer advantages in many situations, in the post-disaster debris

cleanup environment, the potential benefits are either disadvantages themselves or outweighed

by other disadvantages. The inherent nature of post-disaster recovery does not seem to fit well

within a progressive articulation framework. Most importantly, additional time involved

resulting from repetitive cycles of interactions with DMCs and increased computational

requirements of progressive and posteriori methods, would lead to delays that would only worsen

an already difficult situation.

2.5 Statistical Process Control

Statistical process control (SPC) methods have been well studied in the literature for nearly a

century. The basic purpose of SPC is to detect process variability that results not from in-control

or normal random variation of a process (common cause variability), but from out-of-control or

systematic variation of process (special cause variability). As Hawkins and Olwell (1998)

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describe, systematic or special cause variation can be either *isolated* or *persistent* in nature. Isolated (sometimes called transient) variability occurs when a sample measurement signals out-of-control (exceed in-control thresholds) and then returns to in-control readings after only one or a few sample measurements only to signal out-of-control again in the future. The well-known Shewart Xbar and R charts compare measurements to in-control limits at each successive sample period and are used to effectively identify processes that have shifted out-of-control when this isolated variability leads to large shifts in process parameters. Persistent variability, on the other hand, occurs when a sample measurement signals out-of-control and remains out-of-control until an adjustment is made to the process. The well-known cumulative sum (CUSUM) chart compares the cumulative deviation measurements to in-control limits at each successive sample period and is used to effectively detect processes that have shifted out-of-control as a result of smaller, but more persistent variability (Hawkins and Olwell 1998, Ryan 2000).

Generally, SPC process measurements are taken at intervals over time and compared against the in-control process average either visually using a chart or in tabular format using a decision interval approach. If the measurements fall outside a pre-determined acceptable number of standard deviations, then a signal is generated and the process is said to be out-of-control. More specifically, the process commonly consists of two parts: (1) phase I methods, which are used to estimate in-control process measures of mean and variance, and (2) phase II methods, which include gathering sample measures and determining if and when a process has gone out-of-control (Hawkins et al. 2003).

When analysis into special cause variability is carried out on a finite set of historical measurements, the data analysis is said to be retrospective in nature. In contrast, methods used to detect special cause variability in real-time as data becomes available or emerges are said to be

prospective in nature (Chang et al. 2008, Rogerson 2001). Real-time detection is important in many situations, especially where postponing analysis would result in unnecessary or unacceptable cost and in cases where timeliness of detection and correction activities is critical. As a result, prospective SPC is used in applications ranging from manufacturing to healthcare to homeland security (Chang et al. 2005, Chang et al. 2008, Duczmal et al. 2006, Hart et al. 2006, Rogerson and Yamada 2004, Russell and Taylor 2009, Watkins et al. 2008, Woodall 2006).

Retrospective SPC methods are typically well-suited for estimating the baseline or in-control process measures. In this case, either available historical data can be used or a sub-set of the data can be used to accurately generate in-control parameters that can be used for Phase II methods. Prospective SPC, on the other hand, is not well-suited for typical Phase I methods. In cases where the process of interest is ongoing or occurring in real-time, historical information may not be available, design or performance specifications may be unknown, or the cost and time of generating estimates may be impractical. In these cases, such as the debris cleanup problem we study here, alternative data analysis methods can be used to determine out-of-control shifts in process parameters.

SPC research into such alternatives to traditional Phase I methods has been and continues to be of interest in the literature (Grigg and Spiegelhalter 2008, Hawkins et al. 2003, Hawkins and Maboudou-Tchao 2007, Kulldorff 2001, Rogerson 1997, Zantek 2006). Hawkins (1987) first proposed a self-starting cumulative sum (SS-CUSUM) method, which uses ongoing process measurements to calculate the in-control parameters, and demonstrated that it achieved excellent results even when compared to a CUSUM chart with known in-control parameters. Quesenberry (1995) proposed a CUSUM of Q statistics claiming statistical advantages over Hawkins' approach for controlling the desired average run length (ARL) or the average time that the

CUSUM generates an out-of-control signal. Recently, Zantek (2006) studied the performance of the CUSUM of Q method recommending decision interval parameters that also lead to better performance than traditional CUSUM methods. More recently, Grigg and Spiegelhalter (2008), proposed an empirical estimate of the in-control parameters of the CUSUM and suggested using it following a false discovery rate (FDR) approach for systems with large number of sub-processes. Hawkins et al. (2007) proposed a self-starting approach for the exponentially weighted moving average (EWMA) method and showed effective performance even when compared to traditional methods and known estimates. Other related work has investigated the effect of sample size on estimating in-control parameters in the absence of traditional Phase I methods (Reynolds and Stoumbos 2004).

Because the self-starting CUSUM assumes that measurements are independent and identically distributed normal random variables, autocorrelation is a concern. The most common method for dealing with autocorrelation, which we follow in this study, is to perform the CUSUM on measures that have been transformed into well-known statistically independent residuals (Hawkins and Olwell 1998). Atienza et al. (Atienza et al. 2002) propose a CUSUM that uses untransformed process measurements and show that it results in nearly as good as those using transformed measures when the measures are serially correlated. Liu and Wang (Liu and Wang 2008) propose a new CUSUM for detecting shifts in auto correlated data and show that it achieves excellent results even when measurement errors are large.

When there are multiple variables of interest—the multivariate case—correlation among variables becomes a concern. Research related to multivariate methods has gained interest in the literature (Bersimis et al. 2007, Chang, Zeng and Chen 2008, Hawkins and Olwell 1998, Hawkins and Maboudou-Tchao 2007, He and Grigoryan 2005, Pignatiello and Runger 1990,

Rogerson and Yamada 2004, Zamba and Hawkins 2006). Bersimis et al. (2007) provide an excellent detailed overview of multivariate statistical process control charts. Pignatiello and Runger (1990) provide comparison multivariate CUSUM charts and show that their performance depends upon the nature of the shift in process parameters. Important to our study here, Rogerson and Yamada (2004) compare using a multiple univarite CUSUM approach with a multivariate CUSUM approach for monitoring disease patterns across an area comprised of many sub-regions. They show that when the correlation between regions is low, the multiple univariate approach performs better than the multivariate approach in detecting changes in a relatively small number of regions.

Chapter 3

Incorporating Recycling into Post-Disaster Debris Disposal

Abstract

Although large amounts of disaster-generated debris significantly strain landfill capacities, until recently, existing policy provided no financial incentive to consider other disposal alternatives such as recycling. In 2007, FEMA released a new pilot program that provides incentives for communities to recycle by allowing them to retain revenue from the sale of disaster debris. This first-ever policy offers significant financial benefits for communities seeking to clean-up in an environmentally responsible way but requires reexamining existing assumptions and decision processes that are based on prior reimbursement programs. This paper presents a decision model with recycling incentives for locating temporary disposal and storage reduction (TDSR) facilities in support of disaster debris cleanup operations. A facility location model is proposed to incorporate the unique assumptions, objectives, and constraints of disaster recovery in light of FEMA's new policy.

Keywords: disaster management, disaster debris, disaster recovery, recycling, facility location

3.1 Introduction

Recent natural disasters such as Hurricane Katrina have underscored the importance of sound emergency management for successfully responding and rebuilding in the wake of catastrophe. Two of the most important and initial aspects of disaster response and recovery operations are the removal and disposal of debris from the disaster-affected area. Although the nature of debris or waste can vary depending on the type of disaster, disaster debris is often a mixture of most or all of the following: general household trash and personal belongings, construction and building

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materials, trees, vegetative and organic waste, hazardous waste, appliances, and electronic devices. All of these categories of waste have their individual challenges for disposal even under normal conditions, and additional disaster-caused combinations of these types often create new mixed-categories with increased complexities for separating, cleaning, and disposing of the waste (Roper 2008).

In addition to the types and composition of the debris, the amount of debris—which can easily exceed several times the amount of debris generated under normal conditions—instantly overwhelms traditional solid-waste disposal systems. For example, in only a few hours, Hurricane Katrina generated more than 50 times the annual amount of debris disposed in landfills under normal conditions (Stephenson 2008).

Not surprisingly, the cost of debris disposal can be substantial, accounting for more than 27% of total disaster costs (FEMA 2007). In the case of Hurricane Katrina, the U.S. Army Corps of Engineers (USACE) awarded $1.5 billion in contracts for debris removal just days after the storm made landfall as a category 4 hurricane. Although recovery operations are still ongoing after nearly 5 years, the total cost of debris cleanup alone has totaled more than $4.4 billion (Stephenson 2008).

As a result of the sizeable costs and the reliance on federal financial assistance, disaster debris disposal operations are driven by federal reimbursement policies and guidelines most commonly administered by the Federal Emergency Management Agency (FEMA). Generally, FEMA will reimburse 75% of the costs of debris disposal, leaving the remaining 25% the responsibility of local municipalities. In the case of Presidential emergency declarations, 100% of costs may be eligible for reimbursement during limited time periods (FEMA 2007).

Until recently, FEMA reimbursement policy focused exclusively on reimbursing costs of disposal—collection and transportation costs, temporary disposal and storage reduction (TDSR) operations, and project management—while discouraging recycling by requiring that total reimbursement be reduced by the amount of proceeds from the sale of all recycling activities (FEMA 2007). In August 2007, FEMA changed its policy and announced a program offering financial incentives for municipalities to encourage recycling and reuse of disaster debris (FEMA 2008). The new policy permits municipalities to retain all proceeds from recycling activities without any restrictions, offering local governments the opportunity to effectively reduce their portion of the cost of debris disposal.

There are two objectives of this paper. Our first goal is to identify the differences between disaster debris cleanup and every day solid waste disposal, which we call the Disaster Debris Cleanup Problem (DDCP). Our second goal is to develop a facility location model that incorporates FEMA's new recycling incentives and assists disaster management coordinators with locating TDSR facilities. Our aim is to develop a model that could be used in disaster planning or in developing initial plans immediately following a disaster as damage estimates become known. With these goals in mind, the remainder of the paper is organized as follows: Section 2 provides a brief review of the literature related to facility location and disaster management. Section 3 describes the unique characteristics of the disaster debris cleanup problem (DDCP) and the challenges of locating TDSR facilities. Section 4 formulates the TDSR Disaster Location Problem (TDSR-DLP) with recycling incentives as a facility location problem. Section 5 offers conclusions and describes future research plans.

3.2 Literature Review

Facility location has been the focus of considerable research for nearly a century since it was introduced by Alfred Weber as the problem of locating a warehouse (facility) in order to minimize a weighted-distance from customers (demand)—what has become the well-known "Weber Problem" (Brandeau and Chui 1989, Drezner 1992, Drezner 1999, ReVelle et al. 2008). In general, the objective of the facility location problem is to locate one or more "facilities" among a collection of possible, spatially-distributed locations in order to satisfy some objective with respect to "demand," an objective that has evolved over the years to include cost, time, and other factors in addition to distance measures.

Although still used in determining locations for warehouses and manufacturing facilities, facility location has been used in many diverse applications with broad meaning of the notion of "facility." The use of facility location models for locating ambulances, fire stations, taxicab fleets, helicopter landing areas, radio signaling towers, nuclear power plants, and health centers are among the many articles in the literature (Daskin and Stern 1981, Lee et al. 2006, Pirkul and Schilling 1988, Saadatseresht et al. 2009). Several summaries of location research have been published over the years, and interested readers are directed to Brandeau and Chui (1989), Klose and Drexl (2005), ReVelle et al. (2008), Hamacher and Nickel (1998), and Owen and Daskin (1998).

Facility location models can be broadly categorized, on one hand, as either discrete, continuous, or network models depending on the decision space for demands and locating facilities. Identifying the decision space is commonly used for organizing and identifying possible solution methodologies. In the continuous case, facilities can be located anywhere in the decision space as contrasted with the discrete case, which chooses from a discrete set of

possible locations. Both continuous and discrete location models assume that demands occur at

discrete locations, while network models assume demands occur on a collection of connected

nodes (Brandeau and Chui 1989, ReVelle et al. 2008, Sahin and Sural 2007).

Location models can also be broadly categorized in terms of their objective function—for

example, whether to minimize the maximum distance between any demand point and facility (P-

center model), or to locate facilities within some specified distance from demand points

(Location Set Covering and Maximal Covering Location Models), or to minimize the average

distance between demand points and facilities (P-median model). The first two examples—the

P-center and Covering models—are generally referred to as equity-based objective models while

the latter example—the P-median model—is referred to as an efficiency-based objective model.

Objective-based classification is helpful in classifying, evaluating, and formulating appropriate

models for specific application domains and problems (Brandeau and Chui 1989, Drezner and

Hamacher 2002, Hamacher and Nickel 1998, Jia et al. 2007, ReVelle et al. 2008, Sahin and Sural

2007).

Many extensions to these basic models have been proposed. Of particular interest to our

study here is the Fixed-Charge Location Problem (FCLP), which developed from the basic P-

median model formulation. In the basic formulation of the FCLP, a fixed-cost is added to the

original variable cost objective (usually consisting of transportation costs) and the constraint

requiring the number of facilities to be located is removed from the general P-median model.

Subsequently, the optimal number and location of facilities is determined as the cost objective is

minimized. As Owen and Daskin (1998) describe, extensions to this general FCLP model

include allowances for capacity limitations, demand assignment restrictions, and other location

attribute requirements.

Although the term "emergency management" (EM) has been used in the literature to describe a wide range of activities from identifying optimal locations for daily ambulance coverage to identifying the most efficient routes for hurricane evacuation, emergency management of disasters and catastrophic events differs significantly from management of routine or daily emergencies (Altay and Green 2006, Quarantelli 2001). Our focus in this study, hurricane debris disposal, is one of the most important aspects of the least researched area of disaster management—post-disaster, recovery phase activities (Altay and Green 2006). Towards this purpose, we use the terms disaster management (DM) and disaster operations management (DOM), which best reflect the nature of our study.

There is increased interest in DOM especially since 9/11 and Hurricane Katrina (Simpson and Hancock 2009). While the majority of published research has focused on pre-disaster activities, such as mitigation and evacuation, considerably less research has studied post-disaster response activities such as distributing food and rebuilding infrastructure. For example, recent pre-disaster studies have developed models for protecting water supply systems (Qiao et al. 2007), improving airline security (McLay et al. 2007), and developing effective evacuation plans (Saadatseresht et al. 2009), while recent post-disaster studies have developed models for allocating ambulances to disaster relief operations (Gong and Batta 2007) and restoring disaster-damaged electrical power systems (Cagnan and Davidson 2007).

Despite the increased interest and recent journal articles related to disaster recovery, management, and relief, the problems and challenges of debris management have primarily been explored qualitatively in the literature—offering valuable insight and analysis mostly through case studies of specific events. For example, Roper (2008) examined debris and waste management activities and policies involving the cleanup from Hurricane Katrina. He confirms

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the importance of debris disposal planning and cleanup operations to successful recovery and rebuilding activities, specifically focusing on opportunities and proposed changes for increasing recycling and reuse. Others have observed or studied debris and waste management surrounding recent earthquakes, hurricanes, landslides, and wars, also underscoring the importance and the need for debris planning and support (Emerson 2004, Farrell 1999, Jerome 2005, Lauritzen 1998, Popkin 1986, Reinhart and McCreanor 1999, Roper 2008, Swan 2000, Trimbath 2005, Wei et al. 2008).

Quantitative studies involving disaster debris management are few, generally relating to aspects of planning and mitigation. For example, Wei et al. (2008) propose a hazard mitigation decision support system using simulation to predict debris flow movements in the event of a landslide. Jakob (2005) offers a 10-fold classification scheme for debris flows that incorporates topography and peak discharge volume aimed at providing valuable assessment information useful in mitigation activities for highways, bridges, pipelines, and other infrastructure.

3.3 Disaster Debris Cleanup Problem (DDCP)

Disaster debris cleanup operations are commonly organized into two phases (FEMA 2007). During the first phase, the objective is to clear debris from evacuation and other important pathways to ensure access to the disaster-affected area. Practically, Phase 1 activities largely consist of pushing fallen trees, vehicles, and other debris blocking streets and highways to the curb. These activities begin immediately once the disaster has passed with the goal of completion usually within 24 to 72 hours. In Phase 2 of debris removal, which is the focus of our study here, completion can take months or longer. Activities in this phase include organizing and managing curbside debris collection, reduction, recycling, and disposal operations (City of

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Chesapeake 2007, FEMA 2007). For purposes of this study, all references to debris cleanup activities are intended to mean Phase 2 activities unless specifically stated otherwise.

At first glance, it may appear as though everyday solid-waste collection practices would apply directly to disaster debris cleanup. Solid waste disposal operations have been studied extensively in the literature. In general, the problem has the following basic characteristics: waste is collected from demand points; transported to transfer stations for reduction, separation, or recycling; and either reused or transported to a landfill or incinerator for final disposal. Generally, waste is collected from demand points using relatively smaller capacity (more costly) vehicles as compared to larger, tractor-trailer (less costly) vehicles used to move waste from transfer points to final destinations. It follows that the aim is to locate final disposal facilities (landfills, incinerators, etc.) far enough away from demand points and to locate transfer stations in such a way to achieve optimal cost. Caruso et al. (1993) propose a capacitated fixed-charge location allocation problem for modeling urban solid waste in Italy. Others have also proposed mixed integer formulations to minimize distances and collection and facility costs (Antunes 1999, Caruso et al. 1993, Chang and Wang 1996, Eiselt 2006, Khan 1987). MacDonald (1996) offers an excellent review of solid waste management models.

A closer analysis, however, highlights the need for research specifically focused on disaster debris cleanup. We draw upon the differences between everyday emergency management and disaster management as described by Quarantelli (2001) and offer the following ways that disaster debris collection and disposal differs qualitatively and quantitatively from everyday solid-waste collection and disposal:

1. Local municipalities are immediately overwhelmed and must quickly relate to many other, often unfamiliar organizations responding to the disaster that are not a part of

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everyday solid-waste or routine debris collection activities. These organizations may include other federal, state, and local government agencies, public utilities, contractors, and sub-contractors. In a disaster, huge numbers of contractors and sub-contractors all converge at the disaster area—a phenomenon that does not occur in routine solid-waste and debris collection, which typically involve only resources from the municipalities' public works department or one, usually long-term, solid-waste contractor.

2. In large scale disaster debris removal and disposal operations, municipalities lose independence and freedom as federal, state, and other local municipalities' requirements, needs, and values become more important than individual autonomy. For example, disposal operations are driven by FEMA reimbursement requirements, which are implemented as part of federal disaster declaration.

3. Because of extreme amounts of debris resulting from a disaster—often exceeding several years of debris collected on a routine basis—municipalities are subject to very different performance standards. In everyday solid-waste disposal, the amount and location of waste is either known or can be reasonably predicted for efficient allocation of resources. Following a disaster, the volume and locations of debris are unknown and estimates are often not accurate. In fact, the most widely used tool for estimating debris volume provides estimates within a 30% margin of error. Volume and location information tends to emerge as cleanup operations are carried out. These factors lead to three important considerations. First, instead of offering a minimum level of curbside debris collection, typically one day a month as in everyday solid waste collection, the objectives in disaster debris operations focus on distributing maximum available resources equitably across the affected area while simultaneously seeking to minimize time and cost of cleanup.

Second, because of the uncertainty surrounding demand, disaster coordinators route collection vehicles to both primary and alternate TDSR facilities in order to improve operational efficiency during congestion. In everyday solid waste collection, the need for alternate TDSR assignments would be extremely rare. Third, existing landfill capacities are typically exceeded by more than several years' capacity or at least become significantly strained. Subsequently, Temporary Disposal, Storage, and Reduction (TDSR) facilities, which perform reduction, separation, and recycling (RSR) activities, are needed to handle enormous debris volumes, maximize FEMA reimbursement, and improve efficiency and timeliness of disposal operations. As a result, decision makers are challenged to locate as many TDSRs as necessary in or at least close to the affected region. In the case of everyday solid waste collection, objectives generally include seeking to locate landfills and transfer stations as far away from the collection area as possible (Bautista and Pereira 2006, Eiselt 2006, Eiselt 2007).

4. In disaster debris disposal operations, public and private organizations interact at a faster and closer level, circumventing every day policies and practices. Because disaster-generated debris often results in mixtures that are uncommon, it creates complexities that make it difficult to comply with landfill separation and disposal protocols followed under normal conditions. As a result, standard operating procedures for disposal (separation, recycling, and permitted landfill debris types) are often relaxed or overlooked in lieu of cleaning up the area as fast as possible. Frequently, policies for contracting and bidding are also often bypassed in order to more quickly obtain needed resources.

These differences between everyday solid-waste collection and disaster debris cleanup lead to important modeling considerations. First, in debris cleanup operations, decision makers must

consider larger, strategic recovery objectives of restoring economic, social, and political infrastructures in addition to operational and tactical objectives. In other words, as in Phase 1 cleanup activities, speed of debris removal remains an important consideration in Phase 2, but now additional objectives such as equitably allocating recovery resources, efficiently locating temporary separation and disposal facilities, maximizing recycling, and responsibly managing the overall costs of debris cleanup become increasingly important.

Second, rather than seeking to locate the minimum number of separation and landfill facilities away from the population they serve as is typical of everyday emergency and routine solid waste collection scenarios, a greater or perhaps maximum number of facilities must be located within certain distances to debris affected regions depending upon the nature and magnitude of the disaster and in order to comply with contractor agreements and FEMA reimbursement guidelines. Prior to the new FEMA policy allowing municipalities to retain proceeds from recycling activities, the decision of locating TDSRs—driven by existing FEMA reimbursement guidelines—focused primarily on minimizing variable transportation costs of collecting and transporting debris. For this reason, debris planners typically open an increasing number of TDSRs as the amount of debris increases across the affected area. In this way, the variable costs savings of transporting huge amounts of debris shorter distances outweighs the increased fixed costs of activating additional facilities. Commonly, debris planners rely upon the Saffir-Simpson Hurricane Scale, used in the most widely-used hurricane debris estimating model, as a guide in planning and deciding the number and location of TDSRs (City of Chesapeake 2007, FEMA 2007, Jadacki 2007, Swan 2000). As the category of storm increases, debris estimates across the region increase, resulting in an increased number of TDSRs that are activated across the affected region. However, deciding on which TDSR facilities to activate can

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be extremely costly, hard to reverse, and can have long-lasting effects on the success or failure of recovery activities. Activating too many or too few TDSRs relative to a particular disaster can lead to prolonged recovery, substantial financial burden, or both and can carry with it severe social and political consequences. Complicating matters further is the necessity for decision makers to make these critical decisions quickly when the amounts and locations of debris are at best uncertain.

Another important consideration in debris planning is the role of contractors. Because of the overwhelming nature of disaster, municipalities rely on services provided by independent contractors. Encouraged by FEMA, municipalities will negotiate contracts for debris cleanup activities in advance as part of their debris plan. These contracts, which outline equipment, services, costs, and operational requirements, are subsequently activated as necessary once the disaster event has occurred. Following generally agreed upon best-practices, decision makers typically assign contractors specific areas in order to facilitate organizational control and avoid conflict between competing contractors (City of Chesapeake 2007, FEMA 2007, Jadacki 2007). Contractor assignments and TDSR locations are considered in negotiating contract costs. For example, contractors often charge higher rates to transport debris to TDSRs located at further distances or outside their assigned area as compared to TDSRs located nearby or within their assigned area. Also, contractors who provide multiple services may offer special rates as the number of services they are contracted to perform increases. For example, a contractor may discount standard individual rates for collection, disposal, and TDSR management services if selected to provide all of these services in combination.

3.4 Model Formulation

In general, the Fixed-Charge Facility Location model uses the objective of minimizing the average (total) cost in locating facilities. Furthermore, the Fixed-Charge model and the P-median model that it was derived from are commonly used in situations where the goal is to achieve overall efficiency of all demand points and facilities (Jia et al. 2007, Khan 1987, Owen and Daskin 1998). Disaster planners, for example, would be interested in where to locate TDSR facilities so that the total transportation costs for debris cleanup teams to travel from debris locations to TDSRs is minimized. Lower transportation costs generally result from shorter travel distances, which would allow for more trips each period and result in faster overall cleanup. Shorter travel distances would also help disaster coordinators to maximize FEMA reimbursement. In addition to travel costs, planners would also be interested in how many, what type, and where to locate TDSRs so that fixed opening and closing costs; reduction, separation, and recycling (RSR) costs; and final disposal costs are minimized. Opening and closing costs often include the cost to acquire or lease land, prepare the land for use, and return the land to its original condition. Common RSR methods can include separating, grinding, mulching, compacting, and burning. A TDSR may include a mix of RSR methods (including no RSR) depending on the nature of the disaster and the debris generated and depending on the available equipment and land use capabilities. Finally, in response to FEMA's recent policy change, disaster planners now should consider the effect that recycling operations have upon the decision of what type of TDSRs to activate and where they should be located.

As previously discussed, debris planners also consider both primary and alternate TDSR assignments for debris areas. In addition, planners are concerned with balancing the number and location of TDSRs. All of these factors are important in negotiating favorable contractor

agreements and in helping to minimize the social, economic, and political effects across the affected region. With these considerations, we modify the general fixed-charge facility location model to formulate the TDSR disaster location model (TDSR-DLM).

We consider a set I of regions represented by each region center point and a set J of possible TDSR facility locations. The decision variables for locating TDSRs, assigning regions to TDSRs, and increasing recycling activities are as follows:

Decision variables:

$x_j = 1$ *if TDSR is opened at location j; 0 otherwise*

$z_{ij} =$ *percent of debris from region i to be processed by TDSR at location j*

One of the most important aspects of debris removal operations is forecasting the volume of debris generated by the disaster. Following a disaster, the volume and location of all debris is not known with certainty. In the specific case of a hurricane, the most widely used planning model for estimating the volume of debris is the U.S. Army Corps of Engineers (USACE) model. The USACE model considers the underlying population and other factors such as the storm category, tree canopy coverage, and commercial building density. Using the USACE or another forecasting model, debris demand is included as a parameter to our model in addition to the following:

Parameters:

$M_i =$ *volume of debris in region i (cubic yards)*

$N =$ *maximum number of possible TDSRs to be located in J*

$T =$ *minimum number of TDSRs that must be opened in J*

$\beta_{jk} =$ *percentage of debris to be RSR at TDSR j by method k*

$\gamma_k = reduction\ percentage\ for\ RSR\ method\ k$

$\delta_i = percentage\ of\ debris\ in\ region\ i\ that\ can\ be\ served\ by\ any\ individual\ TDSR(s)$

$c_{ij} = cost\ of\ collecting\ and\ transporting\ debris\ from\ region\ i\ to\ TDSR\ j\ (\$\ per\ cu.\ yd)$

$d_k = cost\ of\ RSR\ for\ method\ k\ (\$\ per\ cu.\ yd)$

$e_k = disposal\ cost\ of\ debris\ RSR\ by\ method\ k\ (\$\ per\ cu.\ yd)$

$r_k = revenue\ from\ debris\ RSR\ by\ method\ k\ (\$\ per\ cu.\ yd)$

$f_j = fixed\ cost\ of\ opening\ and\ closing\ TDSR\ at\ location\ j$

$s_j = fixed\ cost\ of\ RSR\ at\ TDSR\ location\ j$

Note that the last two parameters break out the fixed cost of activating a TDSR into two parts—the fixed cost of opening and closing and the fixed cost of RSR. This granular approach allows decision makers to more easily modify the model to incorporate changes resulting from redesigning a TDSR's RSR capability mix.

The TDSR Disaster Location Model (TDSR-DLM) representing the TDSR-DLP is now written as the following mixed-integer program:

$$min\ Z = \sum_{j \in J} x_j \left(f_j + s_j \right) + \sum_{j \in J} \sum_{i \in I} M_i c_{ij} z_{ij} + \sum_{k \in K} \sum_{j \in J} \sum_{i \in I} M_i \beta_{jk} d_k z_{ij} + \sum_{k \in K} \sum_{j \in J} \sum_{i \in I} M_i \beta_{jk} \gamma_k z_{ij} \left(e_k - r_k \right) \quad (1)$$

Subject to

$$\sum_{j \in J} x_j \leq N \tag{2}$$

$$\sum_{j \in J} x_j \geq T \tag{3}$$

$$\sum_{j \in J} z_{ij} = 1, \quad \forall i \in I \tag{4}$$

$$z_{ij} - \delta_i \leq 0, \quad \forall i \in I, j \in J \tag{5}$$

$$x_j - z_{ij} \geq 0, \quad \forall i \in I, j \in J \tag{6}$$

$$\sum_{k \in K} \beta_{jk} = 1, \quad \forall j \in J \tag{7}$$

$$x_j = \{0,1\}, \quad \forall j \in J \tag{8}$$

$$z_{ij} \geq 0, \quad \forall i \in I, \forall j \in J \tag{9}$$

The goal of minimizing the fixed and variable costs of debris collection, RSR, and disposal across regions while also seeking to maximize recycling income is represented by objective (1). Specifically, the first term in (1) represents the fixed costs of opening and closing TDSRs. The second term in (1) represents the operational costs of removing debris from the affected regions and transporting it to TDSRs. The third term in (1) represents the variable costs of RSR. Finally, income is maximized or loss is minimized from recycling and disposal activities with the inclusion of the fourth term of objective function (1).

Constraint (2) shows that that there is a limit of N TDSRs to be located across all possible locations. This constraint is characteristic of the classic facility location problem that seeks to minimize the number of facilities located. Note that in our uncapacitated location model we assume that each TDSR is able to process all debris from assigned regions.

As is the case in large-scale debris cleanup operations, decision planners often consider a minimum number of TDSRs to open in order to support more effective operations and meet social and political expectations. In order to more efficiently coordinate tactical operations and maximize reimbursement, regions are commonly assigned to specific TDSRs. Representing these practices, constraint (3) requires that at least T TDSRs be opened in the area, and constraint (4) ensures that all of the debris in each region is collected and processed by a TDSR. Constraint (5) allows a decision maker to consider both primary and alternate TDSRs for each region by

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ensuring that no more than δ_i of the total debris in region i is assigned to any TDSR. Constraint (6) requires that debris in each region must be processed by a TDSR that has been opened while constraint (7) ensures that exactly 100% of the debris at each TDSR is reduced, separated, and recycled by all assigned methods k. Constraints (8) and (9) enforce binary and non-negativity requirements of the decision variables.

3.5 Illustrative Examples

In this section, we show how the model can be used to determine the number and location of TDSRs and the assignment of regions to TDSRs for debris cleanup. We consider the area of Chesapeake, Virginia, using historical data from debris cleanup operations following the landfall of Hurricane Isabel in 2003. The data, which includes amounts, locations, and costs for collection operations and TDSR activities, was compiled from records submitted to FEMA for reimbursement under the guidelines of the Stafford Amendment. Hurricane Isabel generated over 900,000 cubic yards of debris, and requests to FEMA for collection, transportation, and RSR operations alone totaled slightly more than \$8 million (City of Chesapeake 2004). In organizing cleanup operations, Chesapeake disaster coordinators divide the area into 49 debris regions for assigning contractors and facilitating operations management. Table 3-1 below shows the debris amounts by region compiled from the Hurricane Isabel data. The data reflect disposal and collection activities before the 2007 FEMA policy that offered financial incentives for recycling. For this reason, the data provide a useful baseline to analyze the impact of the new FEMA policy.

Region	Volume	Region	Volume	Region	Volume	Region	Volume	Region	Volume
1	12,055	11	2,536	21	11,220	31	10,510	41	18,842
2	7,589	12	3,453	22	22,808	32	7,352	42	45616
3	19,077	13	26,093	23	10,503	33	14,169	43	22,319
4	13,372	14	23,466	24	10,203	34	17,257	44	10,315
5	17,723	15	6,825	25	12,800	35	7,943	45	10,772
6	24,529	16	11,365	26	10,186	36	30,525	46	24,086
7	24,675	17	12,342	27	40,240	37	33,821	47	8,842
8	27,214	18	18,486	28	13,074	38	29,777	48	17,920
9	21,294	19	6,661	28	28,094	39	32,835	49	18,508
10	18,235	20	14,874	30	41,169	40	33,078		

Table 3-1: Hurricane Isabel 2003 Debris Volumes (Cubic Yards)

In plans for debris cleanup developed since Hurricane Isabel, Chesapeake officials assign the 49 debris regions to seven TDSR debris areas as shown in Table 3-2 below. Multiple TDSRs can be opened within each TDSR debris area. For example, debris area D has possible locations at Dominion and Shillelagh. For each of the other areas, there is one potential TDSR location as shown in Figure 3-1. The percentage of the total debris in each debris area resulting from Hurricane Isabel is also shown in Table 3-2.

Debris Area	Assigned Debris Regions	Activation Level	% of Isabel Debris
A – Holland	1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 12, 13, 14, 30, 31	1	32.04
B – Elizabeth River	11, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 29	2	17.20
C – Centerville	25, 26, 27, 28	3	8.42
D – Dominion/Shillelagh	32, 33, 34, 35, 36, 37, 48	3	14.23
E – Land of Promise	38, 39, 40, 41, 42, 43, 44	3	21.25
F – Cornland Road	49	2	2.04
G – St. Brides Park	45, 46, 47	2	4.82

Table 3-2: Debris Area Region Assignments

As shown in Figure 3-1, the Chesapeake Debris Plan assigns each debris area to at least one possible TDSR while each region is assigned to exactly one TDSR debris area. In turn, each possible TDSR is assigned an Activation Level, as shown in Table 3-2, that corresponds to the Saffir-Simpson hurricane severity category and is opened according the category storm affecting the area. Possible TDSR locations are shown in Figure 3-1 (City of Chesapeake 2007). In 2003, debris was roughly split between the northern and southern halves of Chesapeake. Initially, one

contractor was hired to begin cleanup operations for the entire Chesapeake area. After a little more than two weeks, as information involving the uncertainty of debris volumes and locations became known, it became apparent that additional resources would be needed. A second contractor was subsequently hired and assigned to the northern section (in 2003, roughly the areas of Holland, Elizabeth River, and Centerville) while the initial contractor was assigned to the southern section (in 2003, roughly the areas of Dominion, Land of Promise, Cornland Road, and St. Brides Park) (City of Chesapeake 2004).
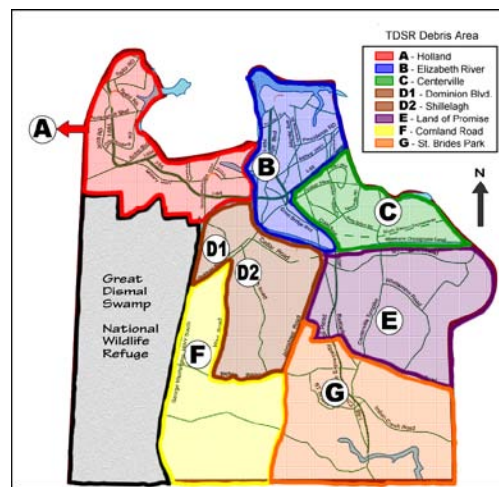
Figure 3-1: Chesapeake Debris Area TDSR Locations (Adapted from City of Chesapeake 2007)

In order to show how the TDSR-DLM can be used in debris planning, we consider three illustrative examples. In the first example, we use the model to solve the TDSR-DLP considering only collection and transportation costs in the objective function. This objective reflects common practices before the FEMA recycling policy. Second, we include fixed and other variable costs as well as income from the sale of RSR debris into the objective. In our third example, we consider the effect that debris demand restrictions have upon the optimal solution and upon primary and alternate TDSR assignments. Finally, we offer analysis of these three examples and highlight the model's usefulness in disaster planning.

To facilitate analysis, we include common RSR methods used by Chesapeake debris planners (City of Chesapeake 2004). Although, there may be other RSR methods depending upon the nature of a specific disaster and the resulting mix of debris generated from the disaster, for our illustrative examples in this study, we use the common input parameter values to our model as outlined in Table 3-3.

(j)	Debris Area TDSR	f_j ($)	s_j ($)	β_{ij} (k=0)	β_{ij} (k=1)	β_{ij} (k=2)
1	A – Holland	15,000	3,000	1.00	0	0
2	B – Elizabeth River	15,000	0	0	0	1.00
3	D1 – Dominion	15,000	5,000	0	0.15	0.85
	D2 – Shillelagh	15,000	0	0	0	1.00
4	F – Cornland Road	15,000	5,000	0.45	0.10	0.45
5	C – Centerville	15,000	5,000	0.85	0.15	0
6	E – Land of Promise	15,000	0	0	0	1.00
7	G – St. Brides Park	15,000	5,000	0.85	0.15	0

Table 3-3: Common Parameters for TDSR Locations

A matrix specifying the cost of collecting and transporting debris from each of the 49 debris regions to each of the 8 possible TDSR locations was created using the lowest values for costs per cubic yard of debris for regions close to a TDSR and increasing values as the distance between each region and TDSR location increases (this matrix is not shown due to its size; however, typical cost per cubic yard ranges from $7.40 to $10). The value of T, the minimum number of TDSRs to be opened in the entire disaster region, is set to 1 in order to allow the model to achieve a minimum objective value solution in each of the three models.

Common practice in disaster debris cleanup is to reduce the initial volume of debris through separation, chipping, burning, grinding, and other methods. The reduced, separated, or recycled volume is then often transported at FEMA's and municipalities' expense to a landfill to be buried or to a commercial company as final disposal. In turn, these commercial companies use the RSR debris to benefit financially. For example, many energy companies receive RSR debris and burn it to produce energy, which is sold to consumers for a profit. Landscape

contractors, building contractors, and land developers receive RSR debris in the form of mulch and grinded stumps and other vegetative debris and use it, in turn, as clean fill or sell it as mulch. Under the new FEMA recycling policy, municipalities can now benefit from these same opportunities by selling RSR disaster debris. We use the following input values for γ_k, d_k, e_k, and r_k as shown in Table 3-4.

(k)	RSR Method	γ_k	d_k ($/yd³)	e_k ($/yd³)	r_k ($/yd³)
0	Chipping	.300	1.00	2.00	4
1	Burning	.025	1.25	9.75	0
2	Grinding	.250	1.25	3.50	4

Table 3-4: RSR Parameters

Solutions to all three of the following examples were obtained using Excel 2007, Frontline Systems, Inc.'s Risk Solver Platform^TM version 9.5 software.

TDSR Disaster Location Model for Collection and Transportation Costs – TDSR-DLM(CT)

The first example we consider includes only collection and transportation costs in the objective. The purpose of this example is to show the effect of recent FEMA recycling incentives when TDSR location and assignment decisions are based on FEMA reimbursement guidelines prior to the new policy. We first set all fixed and variable costs to zero except collection and transportation costs and solve the model. Additionally, δ_i is set to assign each region to a single TDSR (i.e. $\delta_i = 1$). Not surprisingly, all eight TDSRs are opened, and regions are assigned to debris areas exactly as the Chesapeake debris plan outlines shown in Table 3-2 and Figure 3-1 above. Next, all fixed and variable cost parameters from Tables 3-2 and 3-3 are inserted into the above solution to determine the financial impact of the new FEMA policy under the decision objective, which only includes collection and transportation costs. As shown in Table 3-5, 233,373 cubic yards of RSR debris is sold for $933,490—a financial opportunity unavailable before the recent FEMA policy. In other words, if we used the plan developed before 2007,

which focused on minimizing collection and transportation costs, the current opportunity to recycle would save $933,490.

Example 1 - TDSR-DLM(CT)		
	# of TDSRS	8
+	Fixed Opening/Closing Costs ($)	143,500
+	Collection and Transportation ($)	6,813,964
+	RSR Operations ($)	1,044,604
+	Disposal ($)	667,895
-	Recycling Income ($)	933,490
=	Net Cost ($)	7,736,473
	Total Debris Recycled (yds^3)	233,373
	% of Total Debris Recyded	25.6

Table 3-5: TDSR-DLM(CT) Solution Results

TDSR Disaster Location Model with RSR Incentives and Single Assignment – TDSR-DLM(SA)

The purpose of the second example is to consider the impact that the new FEMA recycling incentives have upon the optimal solution if we include recycling as an integral part of debris plan development. In this second example, the model is solved with all fixed, variable, and collection and transportation costs included *a priori*. Similar to Example 1, δ_i is set to ensure that each region is assigned to a single TDSR. The optimal TDSR locations and region assignments are shown in Tables 3-6 and 3-7 and Figure 3-2 below. TDSRs at Holland, Centerville, and St. Bride's Park are opened, resulting in an overall cost of $7,384,134. Note that in comparing Table 3-7 to Table 3-5, by incorporating recycling into the plan *a priori*, we increased our recycling income from $933,490 to $977,514 and decreased overall costs from $7,736,473 to $7,384,134. This difference represents a decrease in cost of more than 4.55%. For a disaster such as Hurricane Katrina in which total debris costs exceed $4.4 billion, cost savings in the range of 4.55% would translate to a total cost savings in excess of $200 million.

While it is not clear that the percentage of cost savings would remain constant for a larger disaster, it could easily increase. The potential is certainly there for substantial savings.

Example 2 - TDSR-DLM(SA)	
Debris Area TDSR	Regions
A–Holland	1–14, 30, 31
B–Elizabeth River	Not Opened
C–Centerville	15–29, 32, 34, 35
D1–Dominion	Not Opened
D2–Shillelagh	Not Opened
E–Land of Promise	Not Opened
F–Cornland Road	Not Opened
G – St. Brides Park	33, 36–49

Table 3-6: TDSR-DLM(SA) Debris Area Assignments

Example 2 - TDSR-DLM(SA)		
	# of TDSRS	3
+	Fixed Opening/Closing Costs ($)	58,500
+	Collection and Transportation ($)	6,862,297
+	RSR Operations ($)	929,657
+	Disposal ($)	511,194
-	Recycling Income ($)	977,514
=	Net Cost ($)	7,384,134
	Total Debris Recycled (yds^3)	244,379
	% of Total Debris Recyded	27.0

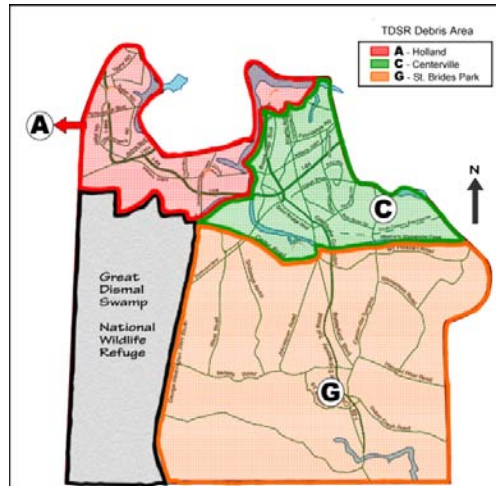**Table 3-7: TDSR-DLM(SA) Solution Results**

Figure 3-2: TDSR-DLM(SA) Debris Area TDSR Locations

TDSR Disaster Location Model with RSR Incentives and Alternate Assignment—TDSR-DLM(AA)

In examples 1 and 2, δ_i was set to equal 1 in order to allow all of the debris in any region to be processed by a single TDSR (primary assignment only). In this third example, the amount of debris that can be processed by a single TDSR is restricted so that each region is assigned to both primary and alternate TDSRs. The purpose here is to reflect contractual requirements and to provide debris field coordinators with information about the most cost effective alternate TDSR choice. With this information, field coordinators can direct collection teams to alternate TDSRs to alleviate congestion and to improve efficiency during the uncertainty of ongoing debris cleanup operations. In this case, TDSRs are opened at the Holland, Elizabeth River, Centerville, Land of Promise, and St. Bride's Park locations, resulting in a total cost of $7,604,765. The solution is detailed in Tables 3-8 and 3-9 and Figure 3-3 below.

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	Example 3	
	TDSR-DLM(AA)	
Debris Area TDSR	Primary	Alternate
A–Holland	1–14, 30, 31	15–29, 33, 48, 49
B–Elizabeth River	---	1–14, 30, 31
C–Centerville	15–29, 32, 34, 35	36, 37
D1–Dominion	Not Opened	Not Opened
D2–Shillelagh	Not Opened	Not Opened
E–Land of Promise	38, 39	40–47
F–Cornland Road	Not Opened	Not Opened
G – St. Brides Park	33, 36, 37, 40–49	32, 34, 35, 38, 39

Table 3-8: TDSR-DLM(AA) Debris Area Assignments

Example 3 - TDSR-DLM(AA)	
# of TDSRS	5
+ Fixed Opening/Closing Costs ($)	88,500
+ Collection and Transportation ($)	6,949,157
+ RSR Operations ($)	968,875
+ Disposal ($)	571,385
- Recycling Income ($)	973,152
= Net Cost ($)	7,604,765
Total Debris Recycled (yds^3)	243,288
% of Total Debris Recyded	26.8

Table 3-9: TDSR-DLM(AA) Solution Results
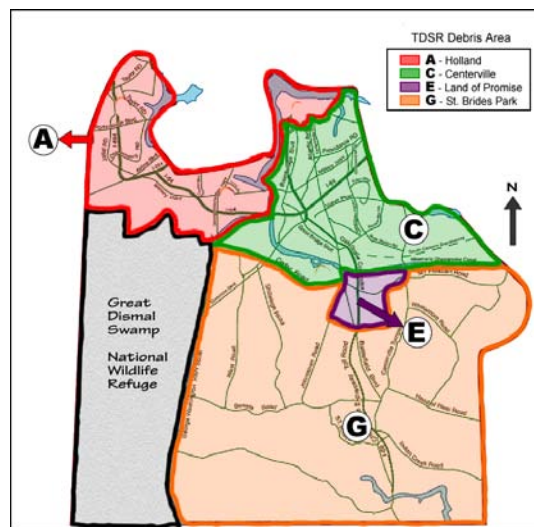
Figure 3-3: TDSR-DLM(AA) Debris Area TDSR Locations

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3.6 Solution Comparison and Analysis

As shown in Table 3-10, Examples 2 and 3 result in identical primary region to area assignments for the Holland and Centerville sites. However, the primary assignments for the St. Bride's Park site differ for regions 38 and 39. Interestingly, when alternate region assignment is considered *a priori*, as in Example 3, the most efficient primary assignment for regions 38 and 39 becomes the Land of Promise site—a site that was not even opened in Example 2. It is also important to note that in Example 3, the Elizabeth River site, also not opened in Example 2, is opened for alternate assignments only. This alternate-only assignment suggests that single-assignment models, which do not consider alternate assignment restrictions, would most likely result in a sub-optimal solution because most disaster debris cleanup operations require decision makers to choose alternate assignments from the set of open TDSRs during ongoing debris cleanup operations. Furthermore, it suggests that single-assignment solutions may result in fewer resources than necessary being allocated to the disaster area—a decision which could prolong cleanup and increase political, economic, and social unrest throughout the affected community. In order to see more clearly the effect of considering alternate assignments *a priori*, we inserted the optimal alternate assignments from Example 3 into the Example 2 solution *post-hoc*. Our *post-hoc* alternate assignments are shown in the "Example 2 – Revised" column in Table 3-10.

Debris Area TDSR	Example 1 TDSR-DLM(CT) Regions	Example 2 TDSR-DLM(SA) Regions	Example 3 TDSR-DLM(AA) Primary	Example 3 TDSR-DLM(AA) Alternate	Example 2 – Revised TDSR-DLM(AA) Regions
A–Holland	1–10, 12–14, 30, 31	1–14, 30, 31	1–14, 30, 31	15–29, 33, 48, 49	33, 48, 49
B–Elizabeth River	11, 15–24, 29	Not Opened	---	1–14, 30, 31	Not Opened
C–Centerville	25–28	15–29, 32, 34, 35	15–29, 32, 34, 35	36, 37	1–14, 30, 31, 36–47
D1–Dominion	32–37, 48	Not Opened	Not Opened	Not Opened	Not Opened
D2–Shillelagh	32–37, 48	Not Opened	Not Opened	Not Opened	Not Opened
E–Land of Promise	38–43	Not Opened	38, 39	40–47	Not Opened
F–Cornland Road	49	Not Opened	Not Opened	Not Opened	Not Opened
G – St. Brides Park	45, 46, 47	33, 36–49	33, 36, 37, 40–49	32, 34, 35, 38, 39	15–29, 32, 34, 35

Table 3-10: Summary of TDSR-DLM Debris Assignments

The detailed results from the Revised Example 2 solution shown in Table 3-11 below highlight the consequences of making decisions based only on single or primary assignments. The revised solution results in the highest collection and transportation costs as well as the highest overall cost. In this revised example, there is nearly the same amount of income from recycling operations, which reflects the similarity in the recycling capabilities of the set of possible TDSRs to be opened. In other situations where open facilities may not have such similar characteristics, there may be much less recycling income and even higher overall costs.

		Example 1 TDSR-DLM(CT)	Example 2 TDSR-DLM(SA)	Example 3 TDSR-DLM(AA)	Example 2 – Revised TDSR-DLM(AA)
	# of TDSRS	8	3	5	3
+	Fixed Opening/Closing Costs ($)	143,500	58,500	88,500	58,500
+	Collection and Transportation ($)	6,813,964	6,862,297	6,949,157	7,254,804
+	RSR Operations ($)	1,044,604	929,657	968,875	932,383
+	Disposal ($)	667,895	511,194	571,385	507,308
-	Recycling Income ($)	933,490	977,514	973,152	964,425
=	Net Cost ($)	7,736,473	7,384,134	7,604,765	7,788,570
	Total Debris Recycled (yds^3)	233,373	244,379	243,288	241,106
	% of Total Debris Recycled	25.6	27.0	26.8	26.6

Table 3-11: Summary of TDSR-DLM Solution Results

3.7 Summary and Conclusions

Hurricane Katrina and other recent disasters have created substantial interest in disaster management research. However, while considerable emphasis has been given to pre-disaster planning and mitigation and to response activities such as evacuation, relatively little attention has been given to studying post-disaster recovery activities, especially activities involving disaster debris cleanup. Only a few qualitative studies have highlighted the importance of and the need for effective management of debris cleanup following a disaster. This paper contributes a quantitative model for solving the TDSR Disaster Location Problem. The first objective of this paper has been to identify the differences between disaster debris cleanup and every day solid waste disposal and to highlight the need for research. The second objective has been to develop a facility location model that incorporates the unique characteristics of disaster debris cleanup and FEMA's new recycling incentive policy for the purpose of assisting disaster management decision makers with locating TDSR facilities. Using data recorded in 2003 from debris cleanup operations that occurred in Chesapeake, Virginia, after the landfall of Hurricane Isabel, three illustrative examples were developed for locating TDSR facilities. These examples highlighted unique aspects of disaster debris cleanup and the financial impact of FEMA's recent recycling policy upon the decision of where to locate TDSRs in support of cleanup operations. This study also underscores the benefits of considering primary and alternate TDSR assignments simultaneously and provides a model for debris planners to use in planning for debris cleanup operations.

3.8 Acknowledgements

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Chapter 4

A Weighted-Tchebycheff Approach to Contractor Assignment in Post-Disaster Recovery Operations

Abstract

Disaster debris cleanup typically accounts for nearly one-third of the total cost of post-disaster recovery. As a result, state and local municipalities rely on federal financial assistance administered by the Federal Emergency Management Agency (FEMA). Ineffective decision making and allocation of resources can severely strain financial resources and cause social and political unrest. Disaster management coordinators must consider multiple objectives when deciding how to allocate resources. This paper presents a multiple objective mixed integer decision model for assisting decision makers in allocating resources in support of disaster debris cleanup operations. A weighted-Tchebycheff goal programming approach is proposed to incorporate the unique assumptions, objectives, and constraints of post-disaster debris cleanup. The effectiveness of the proposed model is demonstrated using data from debris cleanup operations in Chesapeake, Virginia, following Hurricane Isabel in 2003.

Keywords: disaster management, disaster debris, disaster recovery, goal programming, multi-criteria decision making, multiple objective mixed-integer programming

4.1 Introduction

Recent disasters, such as Hurricane Katrina, have underscored the importance of disaster management for successfully responding and rebuilding in the wake of catastrophe. Delays, ineffective decision making, and inequitable allocation of resources can lead to severe social, economic, and political unrest (Roper 2008). Among the most important aspects of post-disaster

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response and recovery operations is the removal and disposal of debris from the disaster-affected area. The amount of debris, which can exceed more than 50 times the annual amount of solid-waste generated under normal conditions, and the need to restore the affected area to pre-disaster conditions in the most timely manner challenge disaster management coordinators (Stephenson 2007). Because of the overwhelming nature of disaster debris cleanup, which demands resources far exceeding the abilities of local municipalities, independent contractors are relied upon to provide additional labor, equipment, and services (FEMA 2007).

Not surprisingly, the cost of debris collection and disposal can be substantial, accounting for more than 27% of total disaster cost (FEMA 2007). For example, in the first several hours after Hurricane Katrina made landfall, over $1.5 billion in contracts were awarded for debris collection and disposal. Today, after nearly 5 years have passed and $4.4 billion have been spent, debris cleanup continues in some parts of New Orleans (Stephenson 2007). As a result of the sizeable costs, local municipalities rely on federal financial assistance. Therefore, disaster debris disposal operations are effectively driven by federal reimbursement policies and guidelines most commonly administered by the Federal Emergency Management Agency. Generally, FEMA will reimburse 75% of the costs of debris disposal, leaving the remaining 25% the responsibility of local municipalities who seek ways to further reduce their portion and subsequently ease their overall financial burden (FEMA 2007).

Encouraged by FEMA, municipalities negotiate contracts for debris cleanup activities in advance as part of their debris planning process. These contracts, which outline equipment, services, costs, and operational requirements, are subsequently activated, as necessary, once a disaster event has occurred. Depending on the severity of the disaster, additional contracts may also be negotiated immediately following the event (FEMA 2007; Stephenson 2007). Following

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generally agreed upon best-practices, decision makers (DMs) typically seek to assign contractors to individual areas in order to facilitate organizational control and avoid conflict between competing contractors (City of Chesapeake 2007; FEMA 2007; Jadacki 2007). Additionally, this objective usually includes an effort to assign areas near to each other (adjacent whenever possible) to each contractor (City of Chesapeake 2007).

The main purpose of this paper is to develop a multiple objective programming (MOP) model that assists disaster management coordinators (DMCs) with allocating resources for post-disaster debris cleanup operations. Our aim is to develop a model that could be used in allocating debris cleanup resources immediately following a disaster and also prove valuable in negotiating pre-contracts as part of disaster planning. With these goals in mind, the remainder of the paper is organized as follows: Section 2 describes the unique characteristics of the disaster debris contractor assignment problem (DDCAP) and the challenges of post-disaster debris cleanup. Section 3 provides a brief review of the literature related to disaster management and multiple objective programming related to aspects important to developing a model to solve the DDCAP. Section 4 formulates the DDCAP as a multiple objective mixed-integer linear program (MOMILP) using a weighted-Tchebycheff goal programming approach. Section 5 demonstrates the model's effectiveness and usefulness to DMCs using data from debris cleanup operations following Hurricane Isabel in 2003. Finally, section 6 offers conclusions.

4.2 Disaster Debris Contractor Assignment Problem (DDCAP)

Disaster debris cleanup operations are commonly organized into two phases. During the first phase, the objective is to clear debris from evacuation and other important pathways to ensure access to the disaster-affected area. Practically, Phase 1 activities largely consist of pushing

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fallen trees, vehicles, and other debris blocking streets and highways to the curb. These activities begin immediately once the disaster has passed with the goal of completion usually within 72 hours. In Phase 2 of debris removal, which is the focus of this study, activities are still focused on removing debris in a timely manner, but additional objectives become the focus of disaster coordinators, notably minimizing the overall cost of cleanup and, most importantly, ensuring that resources are equitably allocated across the affected area in such a manner as to not privilege one region over another because of social, economic, or political influence (FEMA 2007).

Because of the overwhelming nature and significant cost of debris cleanup, local municipalities rely on funding from state and federal agencies and on obtaining additional labor and equipment, which are most commonly contracted from private organizations (FEMA 2007). As a result of reliance on federal funding, FEMA reimbursement policies drive debris cleanup methods and practices. In order to maximize reimbursement, FEMA requires that municipalities develop written debris cleanup plans based upon current policy guidelines and commonly accepted best practices.

An important aspect of disaster debris planning and response is negotiating contracts for additional labor and equipment. FEMA recommends that pre-contracts for debris cleanup resources be negotiated in advance and subsequently activated in response to a disaster event. Specified in the written contracts are the capacity (the number of teams, types of trucks, equipment, etc.) and services (debris collection and transportation, operations and landfill management, etc.) that the contractor will provide and their associated costs (City of Chesapeake 2004; FEMA 2007). Disaster coordinators incorporate this information into their plans for allocating resources depending on the type and severity of a potential disaster event and the potential amount of debris.

The daily volume of debris that can be removed by a contractor (capacity) is a function of the physical capacity of the vehicles, the availability of additional equipment such as chainsaws, front end loaders, etc., and the distance required to transport debris to a disposal site as shorter distances allow for more trips per period. Generally, collection and transportation costs (usually priced by cubic yard) increase as distances between assigned collection areas and disposal locations increase. Therefore, DMCs seek to assign contractors to regions in such a way as to minimize transportation costs.

FEMA (2007) also recommends assigning contractors to regions that are, as much as possible, near to each other and also to refrain, as much as possible, from assigning competing contractors to the same regions. These factors can impact the efficiency and effectiveness of debris cleanup operations. Contractors may also increase fees as the distance between assigned regions increases to cover increased costs, such as the cost of field coordinators and monitors responsible for controlling on-going operations to ensure FEMA compliance for reimbursement, inspecting and certifying loads, and completing FEMA load tickets and project worksheets.

In short, upon the onset of a disaster event, disaster coordinators are challenged to decide how to best assign contractors across the disaster-affected area in order to collect and dispose of debris in the most equitable, timely, and financially responsible way. We call this problem the Disaster Debris Contractor Assignment Problem (DDCAP).

4.3 Literature Review

Since the nature of the DDCAP involves weighing multiple objectives, we first provide a brief review of disaster operations management (DOM) as related to post-disaster recovery and debris

cleanup. Then, we provide a brief review of MOP as related to developing a model for solving the DDCAP.

Disaster Operations Management

Considerable research over the years has focused on emergency management (EM) (Green and Kolesar 2004). While there are similarities between emergency management (EM) and DOM, there are significant and important differences which require the need for additional research (Quarantelli 2001). Our focus in this study, post-disaster debris disposal, is a major aspect of post-disaster recovery, which is the area of DOM in the most need of research (Altay and Green 2006).

Since Hurricane Katrina, there is has been increased interest in DOM research (Simpson and Hancock 2009). However, relatively little attention has been given to debris management in the literature. In one of the few studies, Roper (2008) examined debris and waste management activities and policies involving the cleanup from Hurricane Katrina. He confirms the importance of debris disposal planning and cleanup operations to successful recovery and rebuilding activities, specifically focusing on opportunities and proposed changes for increasing recycling and reuse. Others have observed or studied, mostly through case analysis, debris and waste management surrounding recent earthquakes, hurricanes, landslides, and wars, also underscoring the importance and the need for debris planning and support (Emerson 2004; Farrell 1999; Jerome 2005; Lauritzen 1998; Popkin 1986; Reinhart and McCreanor 1999; Roper 2008; Swan 2000; Trimbath 2005; Wei et al. 2008).

Quantitative studies involving disaster debris management are few, generally relating to aspects of mitigation. For example, Wei et al. (2008) propose a hazard mitigation decision

support system using simulation to predict debris flow movements in the event of a landslide. Jakob (2005) offers a 10-fold classification scheme for debris flows that incorporates topography and peak discharge volume aimed at providing valuable assessment information useful in mitigation activities for highways, bridges, pipelines, and other infrastructure. We are unaware of any studies that investigate decision support methods for assisting disaster coordinators with the challenges of allocating resources to clean up debris such as our study here.

Multiple Objective Programming

Multiple objective programming (MOP) methods have been the focus of extensive study in the literature for quite some time. The majority of multiple objective research studies have focused on multiple objective linear programming (MOLP) methods for solving problems involving continuous variables with objectives and constraints expressed as linear functions (Alves and Climaco 2007). Fewer studies, including those of Rassmussen (1986), Tamiz et al. (1999), and Hallefjord and Jornsten (1988), have focused on multiple objective integer linear programming (MOILP) methods for solving problems with integer restrictions on variables (many of these studies specifically study problems having only binary restrictions). Finally, Alves and Climico (2007) is one of few studies focused specifically on exploring aspects of multiple objective mixed-integer programming (MOMILP) methods for solving problems containing both continuous and integer variables. As Alves and Climaco (2007) point out, while MOILP and MOMILP are closely related, methods used in MOILP do not directly transfer to MOMILP.

In general, MOP methods are commonly grouped into categories depending on the manner in which a DM specifies or articulates his or her preferences with respect to the

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objectives or goals of the problem. MOP methods are classified as prior articulation methods, progressive articulation methods, and posteriori articulation methods (Korhonen 1992).

In prior articulation methods, as Korhonen (1992) and others have described, the DM specifies or makes trade-offs between objectives before model solutions are generated. In other words, the DM preferences are included in the model *a priori*. The major criticism of prior articulation methods in general is the difficulty involved in obtaining accurate preferences from the DM (Hannan 1985). Generally, DMs are asked to rank order or assign weights to objectives in such a way as to indicate their relative importance. While accurately assigning weights or preferences for two or three objectives may be viable in some situations, as the number of objectives increases the task can become nearly impossible (Hwang 1980). As a result, many researchers have proposed methods for assigning weights (Hwang and Yoon 1995). In addition, other progressive and posteriori methods were developed to allow DMs to determine preferences after viewing model solutions.

In progressive articulation methods, rather than require preferences *a priori*, the DM is presented with a set of possible solutions and asked to provide preferences relating to that particular solution set (Korhonen 1992). Using the DM's response, a new solution set is generated and presented to the DM and this interactive process progresses until a preferred solution is obtained. Examples of progressive methods include the STEM, Zionts-Wallenius, and Interactive Tchebycheff methods (Steuer 1989). While progressive methods do not require DM preferences *a priori*, they require much more effort on the part of the DM to participate in the cyclical process and ultimately still depend on the DM's ability to provide accurate preferences to each individual solution set. Providing accurate preferences even when known

solutions are available can still be a very difficult endeavor. It can become even more problematic as the number of solutions increases.

Posteriori articulation methods do not require any assessment from the DM before or during the solution process. As Hwang et al. (1980) and others describe, posteriori methods generate a complete or representative set of solutions from which the DM chooses the one which is preferred. While this process seems beneficial in that no information regarding a DM preferences or utility function is required, the challenge of determining the most satisfactory solution remains. The problem here results from the usually large number of possible solutions that are presented to the DM, which practically make it extremely difficult to accurately make trade-offs in the quest to choose the most preferred solution. Furthermore, generating large sets of solutions can be an extremely complex and time consuming process as computational demands again only increase when integer constraints are added and as the problem size grows (Hwang et al. 1980).

Additionally, both progressive and posteriori methods are more computationally complex and require more time to generate solutions, especially as the size of the problem increases. The addition of integer variables in the problem also increases complexity and solution time. As a result, a major concern is the possibility that a DM may become dissatisfied with the process and abandon it before a preferred solution is generated (Korhonen 1992; Marler and Aroro 2004).

The inherent nature of post-disaster recovery—where time is of the essence and accurate, detailed information is generally unavailable—does not seem to fit well within a progressive or posteriori articulation framework. DMCs are forced to weigh allocation alternatives in the presence of uncertain and often incomplete information—a problem that is only compounded by the need to act immediately. In planning and immediately following a disaster event, it seems

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unlikely that DMCs would be interested or even able to accurately define narrow differences in objective preferences and their corresponding solutions. The time involved in narrowing preferences and evaluating all possible solutions, with prosteriori methods, or repetitively evaluating a smaller number of relatively similar solutions, with progressive methods, would lead to delays that would only worsen an already difficult situation. In the end, the criticisms of prior articulation methods that led to the development of many progressive and posteriori methods are benefits to DMCs in the post-disaster environment.

<u>Goal-Programming</u>

An important aspect of multi-objective decision analysis is the ability of a modeling approach to generate non-dominated solutions. A non-dominated or efficient solution is a solution for which one objective value cannot be increased (improved) without decreasing (worsening) the value of at least one other objective. The assurance of generating the "best" solution based on objective preferences is also of practical importance to DMs. GP methods differ in their ability for generating non-dominated solutions (Hwang 1980; Steuer 1989).

GP is one of the most popular approaches for modeling problems with multiple objectives. Since its introduction nearly 50 years ago, several reviews and criticisms have been published including those by Ignizio (1978), Hannan (1985), and Aouni and Kettani (2001). It is well known that all possible non-dominated solutions cannot be fully enumerated by parameterizing on the weighted objective preferences using the popular weighted-sums (Archimedian) GP approach (Steuer 1989). On the other hand, the MINMAX GP formulation, which uses the weighted Tchebycheff metric, will generate non-dominated solutions (Alves and Climaco 2001).

In general, the weighted Tchebycheff MINMAX-GP seeks to minimize the maximum

weighted deviation of each individual objective from its optimal target value. The optimal target

values for all objectives, which are practically determined by solving for each individual

objective, together form the utopian point in the criterion space (Steuer 1989). After determining

the optimal target values, a DM then specifies his or her preference for each objective *a priori* in

the form of a numerical weight (Tamiz et al. 1998). The Tchebycheff metric subsequently leads

to a contour that defines the non-dominated solution for a particular set of weights as shown in

Figure 4.1 in for a hypothetical MOMILP with two-objectives.
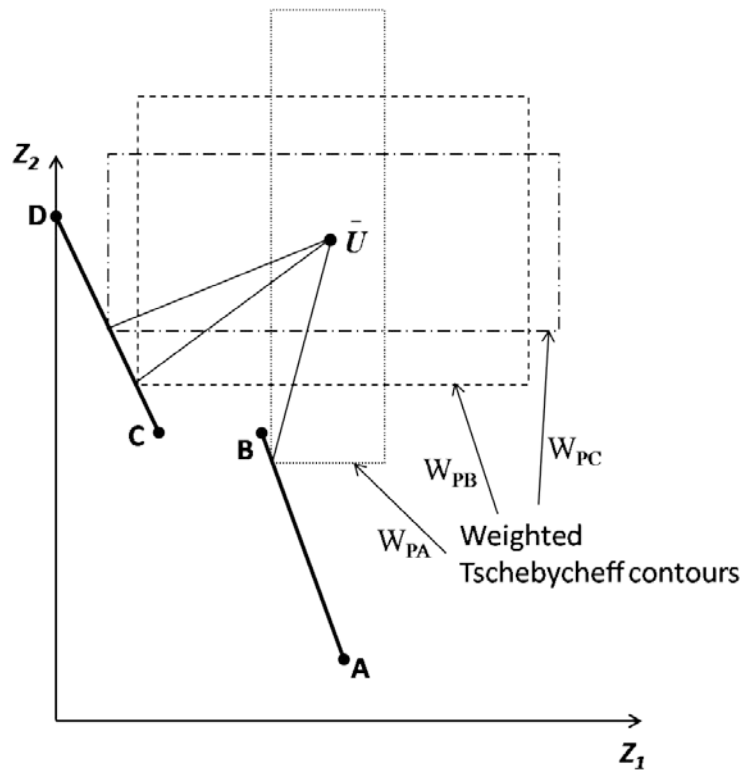
Figure 4.1 Weighted Tchebycheff MOMILP with Two Objectives

In Figure 4.1, the points on line segments AB and CD form the set of non-dominated solutions.

The weighted objectives create a contour that leads from the utopian point, U, to a non-

dominated solution that best reflects those weights or preferences. By changing the weights or

preferences (and resolving the problem), a DM can effectively change the shape of the contour

and generate the non-dominated solution that best satisfies those preferences. In Figure 4.1 above, each contour, W_{PA}, W_{PB}, and W_{PC}, defines one problem solution that best satisfies a specified set of weighted objectives. Bowman (1976) proved that the fully enumerated non-dominated solution set can be generated by parameterization on the weights in both linear and mixed-integer programs. Because of its ability to easily incorporate general objective preferences *a priori* and its ability to generate non-dominated solutions, we follow the weighted Tchebycheff MINMAX GP approach to formulate the DDCAP.

4.4 Model Formulation

For the purpose of achieving the multiple objectives of the DDCAP, we first formulate a multiple objective mixed integer linear program (MOMILP). We consider a set of *J* contractors and a set *J and K* regions, where $J = K$, represented by each region center point. The decision variables and input parameters for assigning contractors to regions and allocating contractor capacity are as follows:

Decision variables:

$x_{ij} = 1$ *if contractor i is assigned to region j*; 0 *otherwise*

$x_{ik} = 1$ *if contractor i is assigned to region k*; 0 *otherwise*

$z_{ij} = $ *percent of capacity from contractor i allocated to region j*

$CVR_{min} = $ *minimum allocated capacity to volume ratio for each region j*

$TD_{max} = $ *maximum distance between regions assigned to any contractor i*

Parameters:

$C_i = $ *total available capacity for contractor i (cubic yards / period)*

D_{jk} = distance from region j to region k (units)

R_j = minimum number of regions that must be assigned to each contractor

T_{ij} = cost for contractor i to collect debris in region j ($ / cubic yard)

V_j = volume of debris in region j (cubic yards)

The three objectives of minimizing total (or average) costs, maximizing the minimum cleanup capacity to debris ratio for all regions, and minimizing the maximum distance between assigned regions for all contractors are initially represented below by the following objective functions and constraints.

Objectives:

$$minimize \sum_{i \in I} \sum_{j \in J} V_j T_{ij} x_{ij} \tag{10}$$

$$maximize \ CVR_{min} \tag{11}$$

$$minimize \ TD_{max} \tag{12}$$

Subject to

$$\sum_{i \in I} x_{ij} = 1 \tag{13}$$

$$\sum_{i \in I} \sum_{j \in J} x_{ij} - R_j \geq 0 \tag{14}$$

$$\sum_{j \in J} z_{ij} = 1, \quad \forall i \in I \tag{15}$$

$$x_{ij} - z_{ij} \geq 0, \quad \forall i \in I, j \in J \tag{16}$$

$$x_{ij} - x_{ik} = 0, \quad \forall i \in I, j \in J, k \in K, where \ k = j \tag{17}$$

$$\frac{\sum_{i \in I} C_i z_{ij}}{V_j} - CVR_{min} \geq 0, \quad \forall j \in J \tag{18}$$

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$$\sum_{j \in J} \sum_{k \in K} D_{jk} x_{ij} x_{ik} - TD_{max} \leq 0, \quad \forall i \in I, j \in J, k \in K \text{ where } j < k \tag{19}$$

$$x_{ij}, x_{ik} = \{0,1\} \quad \forall i \in I, j \in J \tag{20}$$

The objective of minimizing total (or average) costs is represented by (1).

The individual objective to allocate resources in order to equitably clean up the disaster affected region requires specification of the meaning of equity in post-disaster recovery. This notion of equity includes a sense of balance that may be most easily visualized in contrast to post-disaster recovery operations of Hurricane Katrina. In the aftermath of Katrina, less damaged areas received relatively more resources as compared to the most heavily damaged areas as a result of social, economic, and political influence. The inequitable allocation of resources was illuminated as less affected, privileged areas were quickly restored to pre-disaster conditions while the much more significantly damaged, less-privileged areas, such as the 9th ward, still remain in need nearly 5 years after the hurricane made landfall (Roper 2008).

For the purposes of our study, equity is defined as balancing the allocation of resources in such a way that debris cleanup operations are completed in roughly the same amount of time (or at the same rate) across all regions. One method of accomplishing this objective, and the approach which we follow, is to allocate capacity to each region proportionally based on the volume of debris that must be collected. In this way, the higher the allocated capacity to volume ratio, the fewer the number of periods (i.e. days, etc.) are necessary to collect and dispose of debris from the region. In this way, resources are allocated considering the amount of need rather than based on other factors such as social, economic, or political influence. Rather than seeking to maximize the total (or average) capacity to volume ratio for all regions (which may result in some regions having very high ratios and some having very small ratios), we use the MAXMIN approach, which provides a more balanced or equitable result (resulting in more

balanced or similar ratios across regions) (Ogryczak et al. 2008). Therefore, objective (2) and constraint (9) together maximize the minimum per period allocated capacity to debris volume ratio across all regions.

The third objective of minimizing the distance between regions assigned to each contractor is represented by (3) and (10). In this case, we again seek a balanced approach between contractors rather than minimizing the overall (or average) distance for all contractors. While (10) provides the ability to assign contractors to regions close to each other, it creates more computational complexity because the product of x_{ij} and x_{ik} creates a quadratic expression. Following the linearization technique suggested by Plastria (2002), we add a the new decision variable

$y_{ijk} = 1$ *if contractor i is assigned to both regions j and k*; 0 *otherwise*

and substitute $y_{ijk} = x_{ij}x_{ik}$ replacing (10) with (12) below and adding constraints (13), (14), and (15) to the problem.

$$\sum_{j\in J}\sum_{k\in K} D_{jk} y_{ijk} - TD_{max} \leq 0, \quad \forall i \in I, j \in J, k \in K \text{ where } j < k \qquad (21)$$

$$y_{ijk} - x_{ij} \leq 0, \quad \forall i \in I, j \in J, k \in K \qquad (22)$$

$$y_{ijk} - x_{ik} \leq 0, \quad \forall i \in I, j \in J, k \in K \qquad (23)$$

$$x_{ij} + x_{ik} - y_{ijk} \leq 0, \quad \forall i \in I, j \in J, k \in K \qquad (24)$$

Constraint (4) assigns exactly one contractor to each region, while constraint (5) ensures that a minimum number of R_j regions is assigned to each contractor, which may be required because of contract specifications. Constraints (6) and (7) ensure that all available contractor capacity is allocated only to assigned regions. Constraint (8) ensures that all $x_{ij} = x_{ik}$ which is required to properly calculate distances between regions assigned to each contractor in (12). Constraint (11)

restricts the decision variables x_{ij} and x_{ik} to binary variables. Note that it is not necessary to formally restrict y_{ijk} as it will be implicitly restricted to {0,1} through constraints (13), (14), and (15) (Plastria 2002).

Next, we combine the three objectives into one objective using a weighted-Tchebycheff or MINMAX Goal Programming approach (Tamiz et al. 1998). In doing so, we add the following parameters to the problem:

G_T = total cost target for collecting debris

G_C = total capacity allocation target for collecting debris

G_D = distance target between assigned regions

W_T = weight assigned to achieving the total cost target

W_C = weight assigned to achieving the capacity allocation target

W_D = weight assigned to achieving the distance target between assigned regions

Finally, we create a new decision variable Q representing the maximum percent deviation from each goal or target and replace (1), (2), and (3) with the following single objective (16) below. We then add constraints (17), (18), and (19 to the problem.

$$minimize\ Q \tag{25}$$

$$w_T\left(\frac{\left(\sum_{i \in I}\sum_{j \in J}V_j T_{ij}x_{ij}\right)-G_T}{G_T}\right)\le Q \tag{26}$$

$$W_C\left(\frac{G_C-CVR_{min}}{G_C}\right)\le Q, \quad \forall j \in J \tag{27}$$

$$W_D\left(\frac{TD_{max}-G_D}{G_D}\right)\le Q, \quad \forall i \in I \tag{28}$$

The single objective (16) together with constraints (17), (18), and (19) minimize the maximum percent deviation from each of the individual goals or targets, which are practically determined by solving the program for each individual objective. As illustrated in (17), (18), and (19), each objective is normalized as a percentage deviation from its target in order to ensure commensurability of objectives (Steuer 1989; Tamiz et al. 1998). Specifically, constraint (17) restricts the weighted percentage deviation of the cost from its ideal point to Q, (18) restricts each region's weighted percentage deviation from the capacity allocation target to Q for each region, and (19) restricts the weighted percentage deviation from the distance objective to Q for each contractor. Again, one benefit of the MINMAX formulation, and an important reason we choose to use this approach in formulating the DDCAP, is that it is an equity or balancing approach in the sense of seeking to achieve the best worst case scenario for all regions rather than finding the best performance for one region at the expense of another region (Drezner and Hamacher 2002). In the post-disaster recovery environment, this supports the over-arching quest for equity in allocating relative scarce resources to extremely high quantity demands across all affected areas.

4.5 Illustrative Example

In order to demonstrate the usefulness of employing a multiple objective MINMAX approach to solving the DDCAP, we solve the model using data from debris cleanup operations in Chesapeake, Virginia, following Hurricane Isabel in 2003. Hurricane Isabel moved across the Chesapeake area after making landfall across the coast of North Carolina in September 2003 generating nearly 1 million cubic yards of debris and costing over $17 million for collection and disposal (City of Chesapeake 2004).

As detailed in their debris plans, Chesapeake debris coordinators organize the area into 7 debris regions as shown in Figure 4.2 (City of Chesapeake 2004).
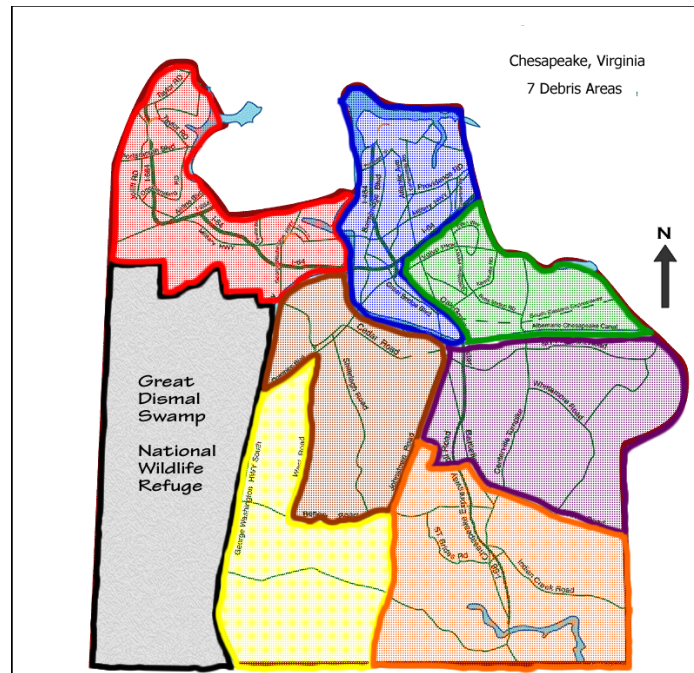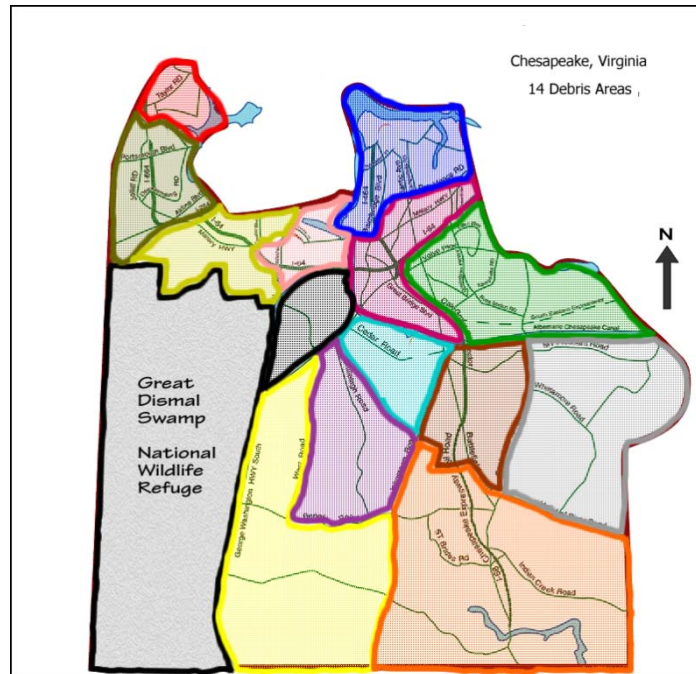

Figure 4.2 Chesapeake Debris Collection Areas

Recall that as part of standard practice, private contractors, specialized equipment, and other resources that may be needed, depending on the severity of the disaster event, are identified and pre-contracts are negotiated as appropriate. In the case of Hurricane Isabel, Chesapeake DMCs initially hired one contractor to assist in debris cleanup. After nearly two weeks of ongoing debris cleanup operations, it became evident that more resources were needed and a second contractor was added to the operations. As outlined in their project reports, one contractor was assigned to the northern regions and the other to southern regions similar to Figure 4.3. In nearly 60 days after the storm hit the region, over 90% of the total debris had been collected and disposed although curbside debris collection operations continued for another 8 weeks albeit at a reduced activity level (City of Chesapeake 2004).
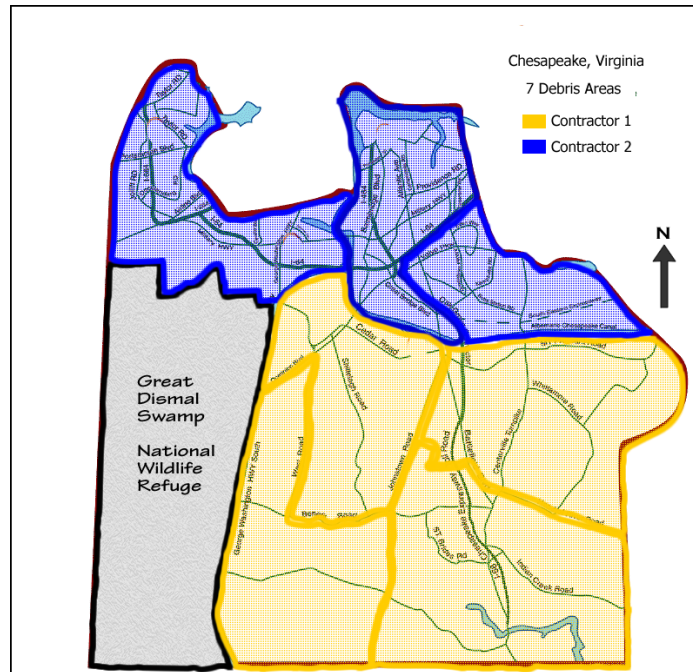
Figure 4.3 Contractor Assignment During Hurricane Isabel

In order to test the model, the 7 debris collection areas identified by Chesapeake planners in Figure 4.2 were further separated into a total of 14 regions as shown in Figure 4.4 below resulting in increasing the number of possible 2-contractor assignments from 128 to 16384. This modification allows evaluation of the performance of the model under a wider range of possible alternatives.

Figure 4.4 Chesapeake Debris Collection Areas Revised for Testing DDCAP

As part of FEMA's requirements for federal cost reimbursement, contractor information, collection and disposal location and times, and capacity and the debris type and volume must be certified by an authorized field monitor at both collection and disposal locations and recorded on a FEMA Load Ticket (FEMA 2007). Using input parameters compiled from FEMA load tickets during Hurricane Isabel cleanup operations in Chesapeake, we first solved the model separately for each of the three individual objectives. In this way, we determined the ideal target or "utopian" values (G_C, G_T, and G_D) required for the weighted-Tchebycheff goal program formulation to obtain an efficient (or non-dominated) solution (Tamiz et al. 1998).

When minimizing the total transportation costs, the model seeks to assign the lowest cost contractors to regions with higher debris volumes. The region assignments for the single-objective minimum cost solution are shown in Figure 4.5 and the objective values in Table 4.1. Figure 4.7 shows the region assignments obtained from maximizing the minimum capacity to volume ratio for each region and Table 4.1 displays the single-objective values. Results from the

remaining single-objective of minimizing the maximum distance between assigned regions for each contractor are shown in Figure 4.6 and also Table 4.1. As expected in minimizing the total (average) distance, the entire area is divided roughly in two and one-half assigned to each contractor appearing somewhat similar to Figure 4.3 except that the locations of contractors are reversed.

Finally, using the ideal target values for each objective, we solve the weighted-Tchebycheff goal program using Microsoft Excel and Frontline Systems, Inc. Premium Platform Risk Solver software. Weights were assigned to reflect the relative importance of achieving the distance goal, G_D, to be twice as important as achieving the cost goal, G_T, and the relative importance of achieving the capacity goal, G_C, to be twice as important as achieving the distance goal, G_D. Contractor assignments are shown in Figure 4.8 and solution results are summarized in Table 4.1.
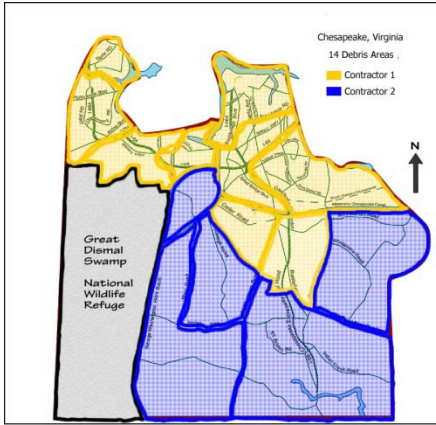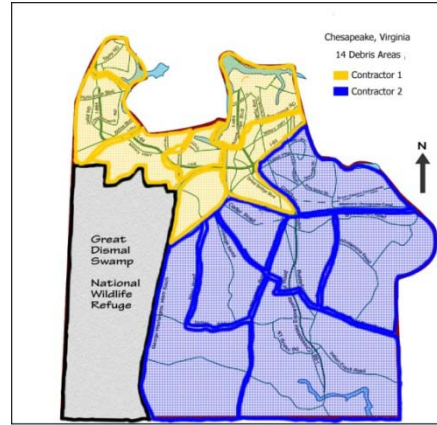
Figure 4.5 Minimize Cost
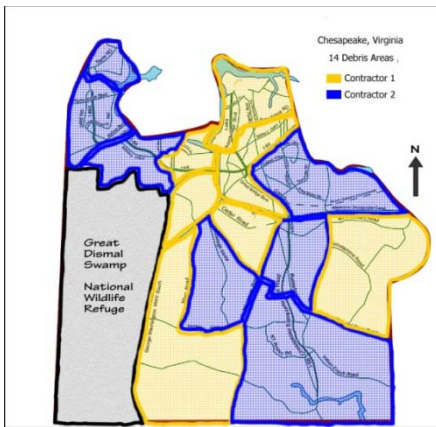

Figure 4.6 MINMAX Distance

Figure 4.7 MAXMIN Capacity
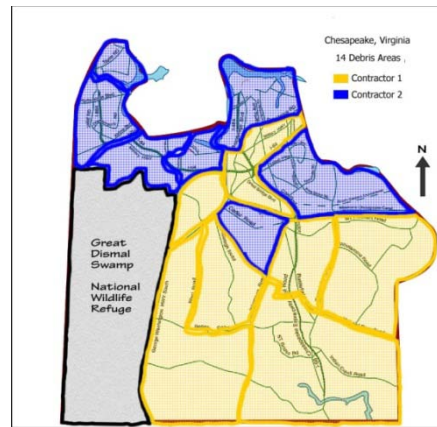
Figure 4.8 Weighted-Tchebycheff Goal Program

Objective	Transportation Costs	Distance (Miles)	Contractor 1 (Days)	Contractor 2 (Days)
Single-Objective Minimize Cost	$6,748,410	199.04	88.87	10.56
Single-Objective MAXMIN Capacity	$6,868,746	165.68	42.92	42.92
Single-Objective MINMAX Distance	$6,895,914	110.67	37.76	53.59
Multiple-Objective MINMAX GP	$6,868,695	123.65	42.94	42.90

Table 4.1 Solution Summary

4.6 Solution Comparison and Analysis

As shown in Table 4.1, the weighted-Tchebycheff goal program (or MINMAX GP) provides the most overall balanced solution, which is preferred in post-disaster debris cleanup. The most important objective of equity, as reflected by balancing cleanup time between regions, is similarly achieved through both the single-objective MAXMIN capacity objective and the multiple objective weighted-Tchebycheff goal programs—both produce solutions that lead to each contractor completing cleanup operations in essentially the same number of periods— nearly a 20% reduction in the number periods from the Single-MINMAX Distance objective.

Considering capacity objectives alone also results in higher transportation costs and nearly three times as much distance between assigned regions for each contractor. This fragmentation in contractor assignments can be easily seen when comparing Figure 4.7 and Figure 4.8. Our analysis here uses, as model inputs, transportation costs that had already been negotiated. It seems plausible, however, that a contractor may demand increased transportation costs as distance between contracted region assignments increases. Furthermore, although only transportation costs were included in this analysis, fragmentation in contractor assignments can easily lead to increased costs for field operations, load inspection, and other services as well. In addition, as previously mentioned, contractor efficiency and effectiveness of debris cleanup operations tends to decline as the distance between assigned regions increases.

While these results might not seem surprising considering that the highest weighted preference was given to achieving the capacity allocation target in the MINMAX GP, it's important to consider the significant benefits of this improved solution. First, while a 20% reduction in the number of periods to complete cleanup—approximately 10 days in the Chesapeake case—may not seem that beneficial, it can significantly improve the success of other

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post-disaster recovery activities, such as reconstruction, and decrease the likelihood of social, economic, and political unrest, which are more difficult to quantify (Roper 2008). Furthermore, a 20% reduction in cleanup time in the case of more severe disaster events, such as Hurricane Ike and Hurricane Katrina, would easily translate into a reduction of a few months to a year or more.

4.7 Summary and Conclusions

Interest in disaster management has increased as a result of Hurricane Katrina and other recent disasters. However, as Altay and Green (2006) point out, relatively few studies have focused on post-disaster recovery problems, such as disaster debris cleanup. Removing disaster debris, which typically accounts for more than 27% of total recovery costs, represents a significant challenge to disaster coordinators who must decide how to best assign resources across the disaster-affected area in order to collect and dispose of debris in the most equitable, timely, and financially responsible way. This paper develops a weighted-Tchebycheff goal program for solving the multiple objective Disaster Debris Contractor Assignment Problem (DDCAP). The weighted goal programming formulation can be solved with standard software and is easy for DMs to understand and use—requiring only that they reflect their relative objective preferences by assigning weights to each objective. Using data from debris cleanup operations that occurred in Chesapeake, Virginia, after the landfall of Hurricane Isabel in 2003, it was shown that significant improvement in the balance of resource allocation, reduction in the overall duration, decreased transportation costs, and increased efficiency in contractor assignment can be obtained when considering the multiple objectives of the DDCAP simultaneously in the proposed weighted-Tchebycheff goal programming model.

4.8 Acknowledgements

4.9 References

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Chapter 5

A Self-Balancing CUSUM Approach for Post-Disaster Debris Disposal Operations

Abstract

As shown by Hurricane Katrina and other recent disasters, disposing of disaster-generated debris can be quite challenging. During Katrina, extraordinary amounts of debris far exceeding typical annual amounts of solid-waste were almost instantaneously deposited across a three-state area. Collection and disposal of disaster debris is an enormous task. Although the locations and amounts of debris can be easily summarized looking back after recovery activities have been completed, they are uncertain and difficult to estimate in real-time. Inaccurate estimates can result in inequitable allocation of resources, increased costs, prolonged recovery, and increased social, political, and economic unrest. This paper uses prospective statistical process control methods—successfully used in prospective detection of disease outbreaks—to achieve equity in allocating debris disposal resources by detecting emerging patterns in real-time as debris information becomes available during disposal operations. Using the self-starting CUSUM method proposed by Hawkins (1987) as a foundation, we develop a self-balancing approach for debris cleanup operations and evaluate its performance using data from a 2003 hurricane.

Keywords statistical process control, cumulative sum, CUSUM, prospective data analysis, disaster debris, post-disaster recovery

5.1 Introduction

One of the most important and initial aspects of disaster recovery operations is the removal and disposal of debris from the disaster-affected area. Disposing of disaster debris can be quite challenging because the debris, which far exceeds typical annual amounts of solid-waste, is

generated almost instantaneously. Also, in the case of large-scale disasters, debris is often spatially scattered throughout a large area encompassing several regions, counties, or states. Hurricane Katrina, which generated the greatest amount of hurricane debris in recorded history, deposited over 118 million cubic yards of debris over an area of 90,000 square miles, which included several states (Jadacki 2007; Hansen et al. 2005). In Louisiana alone, the storm generated over 53 million cubic yards of curbside household debris as compared to 95,000 cubic yards generated annually as a result of normal conditions (Roper 2008).

Although the locations and amounts of debris can be easily summarized looking back after recovery activities have been completed, their overwhelming and immediate nature following the disaster make them very difficult to determine or estimate as recovery operations begin. Disaster management coordinators rely on debris inspection teams to initially survey the disaster area, which basically includes a "sweep" of important intersections, transportation routes, and main thoroughfares (City of Chesapeake 2007; FEMA 2007). However, inspection teams are generally unable to quickly cover or access the entire disaster-affected area to make consistent and accurate debris estimates. Further complicating matters is that the majority of debris occurs on private property and is placed at the curbside by property owners for pick-up by public workers or contractors; a process driven by FEMA reimbursement policies and one that forces disaster management coordinators (DMCs) to rely on estimates from property owners who decide to call the Disaster Operations Center (DOC) or on daily collection and disposal records, both of which provide incomplete information. This uncertain—or worse, inaccurate— information can lead DMCs towards sub-optimal decisions and potentially make a bad situation even worse (Swan 2000). Inaccurate estimates can result in inefficient and inequitable allocation

of resources, increased costs, a prolonged recovery period, and increased social, political, and economic unrest (Roper 2008; Stephenson 2008; Sylves 2008).

As a result of this uncertainty, DMCs are looking for effective ways to accurately estimate debris locations and quantities in order to allocate debris removal resources and equitably cleanup debris across the disaster affected area (Luther 2008; McCreanor 1999). An alternative approach that we propose in this study focuses on using the actual data from on-going debris cleanup operations to address the goal of achieving equity across all affected regions. Rather than relying on estimates, real-time information from debris cleanup teams about debris locations and disposal amounts are used to monitor the process in each region. In turn, each region's performance is compared to a group standard derived from the performance measurements of all individual regions in order to determine whether or not regions are performing equitably.

The purpose of this research is to develop and evaluate a prospective statistical process control (SPC) approach for equitably allocating resources in real-time during large-scale disaster debris cleanup operations. First, we provide a brief review of the literature related to disaster operations management and statistical process control. Next, drawing from the self-starting CUSUM approach in Hawkins (1987), we develop a self-balancing approach designed to assist disaster DMCs with allocating resources in order to achieve equity of cleanup operations across the disaster area. Finally, we evaluate the performance of the self-balancing CUSUM using data from debris cleanup operations following Hurricane Isabel in 2003.

5.2 Disaster Debris Cleanup Operations

Once a disaster event has ended, emergency routes have been cleared, and rescue operations have been completed, the focus of operations turns from saving lives to cleaning up damage, rebuilding, and restoring infrastructure to pre-disaster conditions (City of Chesapeake 2007; FEMA 2006). Time, while still important, is no longer the dominating factor guiding decisions and the overriding objective turns toward equitably cleaning up debris across all regions (Roper 2008). The goal is not necessarily to equally assign the same number of teams to each region, but rather to equitably assign the teams relative to underlying factors such as the amount of debris and the size of the region. Towards this goal, regions that have greater volume of debris would be assigned more total capacity and regions that have lower volumes would be assigned less capacity. In other words, we seek to assign the teams equitably in order to achieve equal performance across all regions—to remove all of the debris from each region in approximately the same amount of time.

Unfortunately, in most cases resource allocation decisions are not easily made because some or all of the determining factors are uncertain or unknown. As previously discussed, the amount of debris, which directly affects the amount of time it takes to cleanup an affected area, is not known with certainty until after all of the debris has been removed. Obtaining accurate estimates are a challenging endeavor and often lead to poor decisions and unwanted results. Even the most widely used model for estimating hurricane debris only produces estimates within 30% of actual volumes (City of Chesapeake 2007; FEMA 2006). Depending on the specific nature of an individual hurricane, relying on these estimates could result in some regions taking several months or years longer than other regions to complete debris cleanup operations. In turn, other important recovery and rebuilding activities could be delayed, and social, political, and

economic unrest could ensue (Roper 2008; Stephenson 2008). Another alternative is to rely on information obtained from ongoing debris cleanup operations and control the overall rate of cleanup, which is the approach we propose to follow in this study.

5.3 Statistical Process Control

Statistical process control (SPC) methods have been extensively studied in the literature for quite some time (Ryan 2000). The main purpose of SPC is to determine if a process is operating in-control by detecting process variability that results not from normal random variation of an in-control process (common cause variability), but from out-of-control or systematic variation (special cause variability). Generally, SPC process measurements are taken at intervals over time and compared against an in-control process average either visually using a chart or in tabular format using a decision interval approach. If the measurements fall outside a pre-determined acceptable number of standard deviations, then a signal is generated and the process is said to be out-of-control. The process commonly consists of two parts: (1) phase I methods, which are used to estimate in-control process measures of mean and variance, and (2) phase II methods, which include gathering sample measures and determining if and when a process has gone out-of-control (Hawkins et al. 2003).

Many SPC methods, which rely on using historical data, have been developed for *retrospectively* determining when a process shifted out-of-control. Retrospective methods have also been developed for estimating in-control process measures (Rogerson 2001). In contrast, *prospective* SPC methods focus on detecting when a process has shifted out-of-control in real-time or as data becomes available (Woodall 2006). Real-time detection is important in many situations, such as post-disaster debris cleanup, where historical information is not available and

in-control measures are unknown, where postponing analysis would result in unnecessary or unacceptable cost and in cases where timeliness of detection and correction activities is critical. As a result, prospective SPC is used in applications ranging from manufacturing to healthcare to homeland security (Chang et al. 2008; Chang et al. 2005; Duczmal et al. 2006).

The well-known cumulative sum (CUSUM) chart, commonly used in prospective SPC, compares the cumulative deviation measurements to in-control limits at each successive sample period to determine if a process has shifted out-of-control (Hawkins and Olwell 1998). CUSUM charts are especially effective in detecting processes that have shifted out-of-control as a result of smaller, but more persistent variability (Hawkins and Olwell 1998; Ryan 2000). The typical CUSUM approach assumes that in-control parameters are known. This approach is useful when there are required design specifications, such as the machining process for cutting material to pre-determined customer specifications, or when historical information is available to accurately estimate the in-control parameters. Unfortunately, in the case of disaster debris cleanup operations and many other situations, accurate information is not always available.

Self-Starting CUSUM Method

The self-starting CUSUM (SS-CUSUM) approach proposed by Hawkins and Olwell (1998) uses data from an on-going process itself to estimate in-control parameters when they are unknown or unreliable. The SS-CUSUM provides excellent performance when in-control parameters are unknown, determines in-control parameters with fewer measurements than typical Phase I estimating methods, and often results in better performance than traditional CUSUM methods when the in-control parameters are known (Hawkins and Olwell 1998).

Hawkins (1987) first proposed a self-starting cumulative sum (SS-CUSUM) method, which uses ongoing process measurements (not historical data) to calculate the in-control parameters, and demonstrated that it achieved excellent results even when compared to a CUSUM chart with known in-control parameters. Because the SS-CUSUM uses ongoing process measurements, autocorrelation is a concern. When there are multiple variables (or regions in our case here) of interest—the multivariate case—correlation between variables becomes a concern. A common method for dealing with correlation is to perform the CUSUM on measures that have been transformed into well-known statistically independent residuals, which is precisely what occurs in the SS-CUSUM method (Hawkins and Olwell 1998).

5.4 Developing the Self-Balancing Approach for Disaster Debris Cleanup

In debris cleanup operations, the disaster area is generally divided into a number of smaller regions in order to facilitate operational effectiveness and control (FEMA 2007). Resources are allocated to each region as directed by DMCs. We seek a performance measure for the CUSUM that best represents equity of ongoing cleanup operations. As previously described, debris cleanup operations primarily involves curbside debris collection from the streets and roads in each region. As a result, we monitor the percentage of road distance covered in each region.

The percentage of total road distance covered or cleaned up in any given region can be easily obtained from daily FEMA collection/load tickets. The road distance that is covered in a particular region during a given period (daily) is dependent upon the total capacity of all debris cleanup teams (DCTs) assigned to the region and the debris density (volume of debris per mile) in the region. In practice, contractors and sub-contractors are used extensively in debris cleanup operations to provide increased cleanup capacity and flexibility in allocating resources in light of

the uncertainty inherent in disaster recovery operations (FEMA 2007). Reflecting this common practice, we assume here that DCTs can be added in a region or removed from a region independent of adding or removing teams in other regions. In other words, the amount of capacity allocated in any region is not dependent upon the amount of capacity allocated to any other region. Subsequently, we use a multiple univariate CUSUM approach, which has been shown to provide better performance than a single multivariate CUSUM when correlation between regions is low (Rogerson and Yamada 2004).

Using the SS-CUSUM approach first proposed by Hawkins (1987), we monitor the percentage of road distance covered in each region against the in-control target. We deviate from the SS-CUSUM approach only in that we use the ongoing measurements from all regions (processes) to calculate one in-control target for all regions rather than using the ongoing measurements to separately calculate an in-control target for each region (process). In this way, we seek a common in-control target for all regions in order to achieve balance in the percentage of road distance covered across all regions. As a result, we call this approach a self-balancing CUSUM (SB-CUSUM) approach. Drawing upon the many benefits of the SS-CUSUM described in Hawkins and Olwell (1998), the SB-CUSUM

- does not require an in-control process mean and standard deviation to be determined or estimated *a priori*;
- allows us to update in-control estimates at each period (sample) with a realistic measure of the cumulative in-control process mean, which is precisely what we need to be able to do in the debris cleanup problem;
- uses the running mean and standard deviation of all regions as the measure for the in-control process measurements for each period,

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- tracks towards the running mean of the overall cleanup process—it also lags behind this overall mean, which is beneficial in the debris cleanup case since we wouldn't want to make snap decisions to increase and then decrease the number of teams in a region continuously in successive periods—so, this feature helps to stabilize or smooth variability in assigning debris cleanup teams over successive periods; and

- provides helpful information about how to adjust the process—for example, an out-of-control upward signal indicates that resources (capacity) in the region should be decreased as more distance is being covered in the region as compared to all other regions. In contrast, a downward signal indicates that resources (capacity) in the region should be increased.

5.5 Estimating the In-Control Target

We follow closely the work of Hawkins (1987) except that we estimate the in-control process mean for the first n sample measurements using the group mean of all regions for each time period calculated as follows in (1)

$$\bar{\bar{X}}_n = \frac{\sum_{t=1}^{n} \bar{X}_t}{n} \tag{1}$$

where $\bar{\bar{X}}_n$ is the running group mean percentage of road distance covered for all regions for the first n sample measurements and $\bar{X}_t$ is the average percentage of road distance covered for all regions in period t calculated as follows in (2)

$$\bar{X}_t = \frac{\sum_{i=1}^{p} d_{it}}{p} \tag{2}$$

where

d_{it} = *percentage road distance covered in region i during period t*

p = *total number of regions*

Therefore, the in-control target or mean road distance covered for the first *n* sample measurements is the average of the percentage of road distance covered measurements for all regions.

5.6 Calculating the Self-Balancing CUSUM for Each Region

Again, we continue to follow the SS-CUSUM approach deviating only in that we use the in-control process mean and standard deviation from the group of processes calculated above rather than from each individual process. Consequently, our approach is subject to the similar assumption that the distance measurements used for accumulating the CUSUM are independent identically distributed (*i.i.d.*) normal random variables for the in-control state.

Recall that we seek to reflect current practice assuming that contracted DCTs can be added or removed from a region independent of other regions. Although reallocation of teams from one region to another may occur as a method for increasing the speed at which regions achieve in-control balance, the debris cleanup problem is clearly not a reallocation problem. Adding or removing teams from a region will most commonly result in increasing or decreasing the total capacity allocated to all regions.

While this is a critical and important distinction addressing the independence among regions, it does not address the dependency concerns between related measurements within each region that arise as a result of the sequential nature of the CUSUM. Hawkins and Olwell (1998) show that using well-known statistical methods to transform a standardized measure of each

sequential sample measurement results in a random variable that is sequentially statistically independent across sample periods.

We use their approach and begin by standardizing each n sample process measurement for $n > 2$ using the in-control running mean $\bar{\bar{X}}_n$ and standard deviation S_n from the same sample observation period as follows in (3)

$$T_n = \frac{X_n - \bar{\bar{X}}_{n-1}}{s_{n-1}}$$ (3)

It is well-known that scaling T_n by $a_n = \sqrt{(n-1)/n}$ leads to the random variable $a_n T_n$, which follows a student t distribution with n - 2 degrees of freedom (Hawkins and Olwell 1998). Following the SS-CUSUM approach, we transform the random variable $a_n T_n$ using equation (4) into a random variable U_n which has been shown to be precisely $i.i.d\ N(\mu,\sigma)$ (Hawkins and Olwell 1998).

$$U_n = \varphi^{-1}(a_n T_n)$$ (4)

In (4) above, φ^{-1} is the normal inverse function. This transformation is critical as it provides us with a random variable to CUSUM that is statistically independent across sample periods.

5.7 Illustrative Example

In order to demonstrate the usefulness of the SB-CUSUM approach for equitably allocating resources during disaster debris cleanup, we apply it using data from debris cleanup operations in Chesapeake, Virginia, following Hurricane Isabel in 2003. Hurricane Isabel moved across the Chesapeake area after making landfall on the coast of North Carolina in September 2003 generating nearly 1 million cubic yards of debris and costing over $17 million to cleanup (City of Chesapeake 2004).

As detailed in their debris plans, Chesapeake debris coordinators organize the area into 7 debris regions (City of Chesapeake 2004). Debris cleanup operations began immediately after Hurricane Isabel passed. Following FEMA guidelines and best practices, DMCs divided the area into two sections and hired two contractors to assist with the cleanup. One contractor was assigned to clean up the northern regions (1, 2, and 3) and the other to the southern regions (4, 5, 6, and 7) as shown in Figure 5.1 (City of Chesapeake 2004).
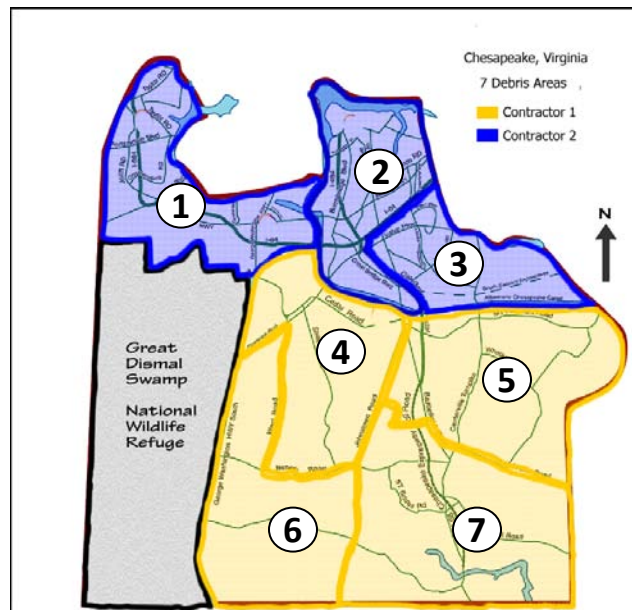
Figure 5.1 Initial Contractor Assignments

According to Chesapeake (2004) project summaries, over 350 trucks were used in the cleanup. In nearly 60 days, over 90% of the total debris generated by Isabel had been collected and disposed. Curbside debris collection operations, however, continued for another 8 weeks albeit at a reduced activity level. This pattern of activity is not uncommon as large amounts of resources are applied in periods immediately following a disaster event and reduced in later periods as cleanup progresses. Perhaps part of the reason for this pattern with debris cleanup is the uncertainty over when to stop curbside cleanup and resume normal everyday solid-waste practices. This uncertainty may stem largely from the uncertainty of debris volume estimates

and the irregular patterns in which property owners may place debris at curbside for pickup. During ongoing cleanup operations, both of these factors influence how well DMCs are able to equitably allocate resources across the area.

Amounts and locations of debris can easily be summarized looking back after debris cleanup operations have been completed. In the case of Hurricane Isabel, the amounts and locations of debris compiled from FEMA debris collection/load tickets are summarized in Table 5.1 below.

Region	Road Miles	Debris Volume
1	194	311,969
2	131	155,918
3	110	76,300
4	128	107,467
5	95	192,782
6	43	18,507
7	26	43,701
Total	727	906,644

Table 5.1 Road Miles and Debris Volumes for Chesapeake Debris Regions

At the time of Hurricane Isabel, there were 727 miles of city roads eligible for FEMA reimbursement of debris cleanup—435 miles in the northern regions 1, 2, and 3, and 292 miles in the southern regions 4, 5, 6, and 7. Using data from Hurricane Isabel cleanup operations and geographic street information for the Chesapeake area, we calculate the road distance for each region as shown in Table 5.1 and initially allocate DCTs (contractor capacity) to regions based on these estimates and the debris volume for each region.

Next, for each period (day) and each region, we record the volume of debris collected and calculate the upward $\left(L_n^+\right)$ and downward $\left(L_n^-\right)$ CUSUM for the self-balancing mean chart of daily road distance covered in each region using equations (5) and (6).

$$L_n^+ = max\left(0, L_{n-1}^+ + U_n - k\right) \qquad (5)$$

$$L_n^- = min\left(0, L_{n-1}^- + U_n - k\right) \qquad (6)$$

where k is the in-control interval allowance for each sample measurement and U_n is the standardized transformed normal random variable representing the standard deviation of the percentage of road distance covered. In other words, each CUSUM, L_n^+ and L_n^-, is updated only by the amount that the standardized deviation U_n exceeds the threshold k (Hawkins and Olwell 1998).

Characteristic of the decision interval CUSUM approach, which we follow, an out-of-control signal occurs when the CUSUM exceeds the decision limit parameter h. The choice of h and k determine the Average Run Length (ARL) of the CUSUM, which is the number of sample measurements from the initial sample up to the sample at which the CUSUM exceeds a decision limit. Also, $2k$ represents the shift in the mean (% distance covered) that we would want to detect (Hawkins and Olwell 1998). For our study here, k was set to 1.5 for the upward CUSUM and -1.5 for the downward CUSUM, in order to detect a shift of 3 standard deviations, and h was set to 1 resulting in an ARL of 142.2 periods (days).

Out-of-control signals must be acted on immediately in order to correct problems contributing to systematic or special cause variation (Hawkins and Olwell 1998). In the debris cleanup case here, an out-of-control signal for the upward CUSUM indicates that the road distance being covered within the region is proceeding much faster than the average of all regions. Practically, an upward signal indicates to the DMC that there may be too much capacity (DCTs) allocated to the region as compared to the amount of debris. Therefore, upon receiving an out-of-control signal for the upward CUSUM, we reduce the number of DCTs allocated to the region by five in order to move the region's cleanup operations towards the in-control average

for all regions. Likewise, upon receiving an out-of-control signal for the downward CUSUM, the number of DCTs allocated to the region would be increased by five in order to move the process towards the in-control average of all regions.

For example, as shown for region 5 in Figure 5.2, an out-of-control signal for the downward CUSUM was triggered in period five. Simulating practical corrective action by the DMC, five additional DCTs were allocated to the region in period 6 bringing debris cleanup operations back into control.
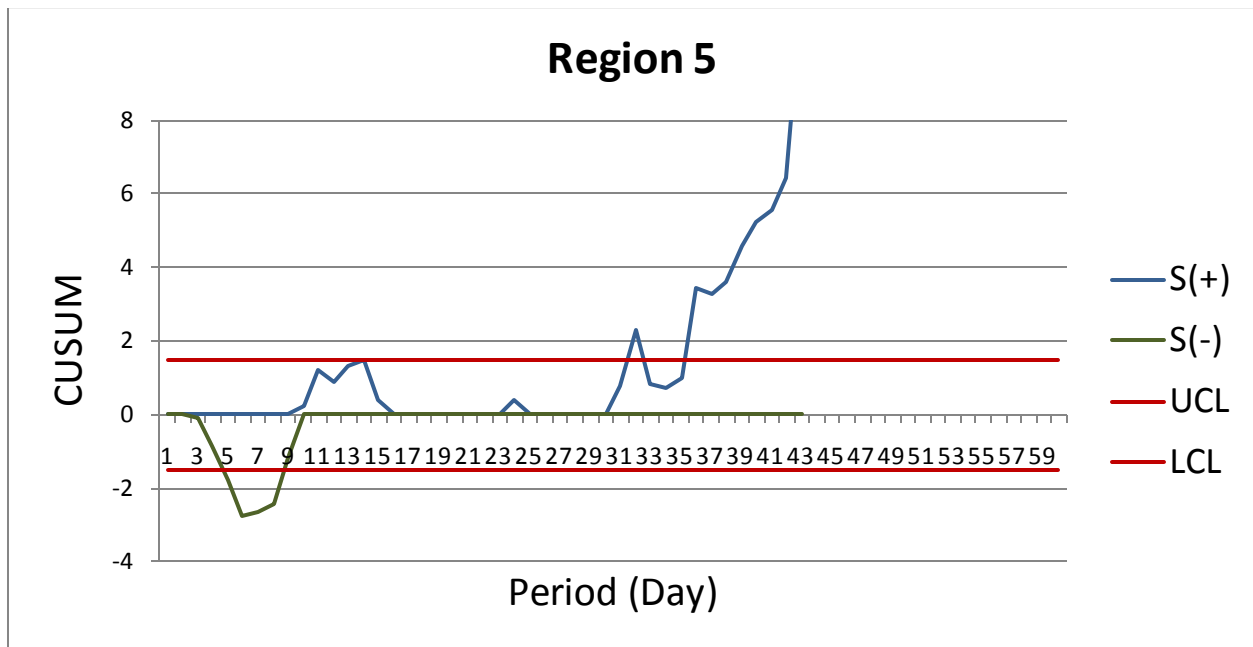

Figure 5.2 Region 5 CUSUM Chart

In period 32, an out-of-control signal for the upward CUSUM is triggered. In this case, five DCTs are removed from the region in period 33 and the process is brought back into control.

For each period, we continue this cycle of recording the debris collected, distance covered, calculating and plotting the CUSUM for each period, and responding to out-of-control signals until all debris has been collected. The amount of debris collected and the number of periods to complete debris cleanup operations are shown in Table 5.2.

| Region	Debris Collected	Periods (Days)
1	311,969	44
2	155,918	42
3	76,300	42
4	107,467	41
5	192,782	43
6	18,507	31
7	43,701	41

Table 5.2 Chesapeake Debris Volumes and Cleanup Times using SB-CUSUM Approach

As shown in Table 2, debris cleanup operations are completed in 44 days—nearly a 35% improvement over the time needed to complete operations without real-time decision support and nearly a 50% improvement over the time of actual cleanup operations in 2003 (City of Chesapeake 2004).

Note also in Figure 5.2 that another out-of-control signal for the upward CUSUM is triggered in period 36, and the percentage of road distance covered in the region remains above the upper control limit until cleanup operations are completed in period 43. Similar characteristics near the end of cleanup operations can be seen as well in Figures 5.4 through Figure 5.9 for the other regions as shown in the Appendix A.

This ending condition reflects the nature of debris cleanup operations—the lower the volume of debris, the lower the debris density, and the greater the road distance that can be covered for curbside pickup. In other words, when the volume of debris remaining for collection reaches a certain level as compared to allocated cleanup capacity, the road distance covered increases substantially even with small reductions in cleanup teams. Practically, as reflected in the data from Hurricane Isabel cleanup operations, overall availability and use of resources seems to fit this pattern: at the beginning of debris cleanup operations, large amounts of capacity become available; the available amount often grows as more contractors and sub-contractors join

in the cleanup; then, as the debris volumes begin to decrease across the area, the pace (amount

of curbside distance covered) increases and sub-contractors and contractors will either leave the

cleanup or be terminated as cleanup operations come to a close. The increase in the percentage

of distance covered in each region as compared to the overall average can be seen in Figure 5.3.
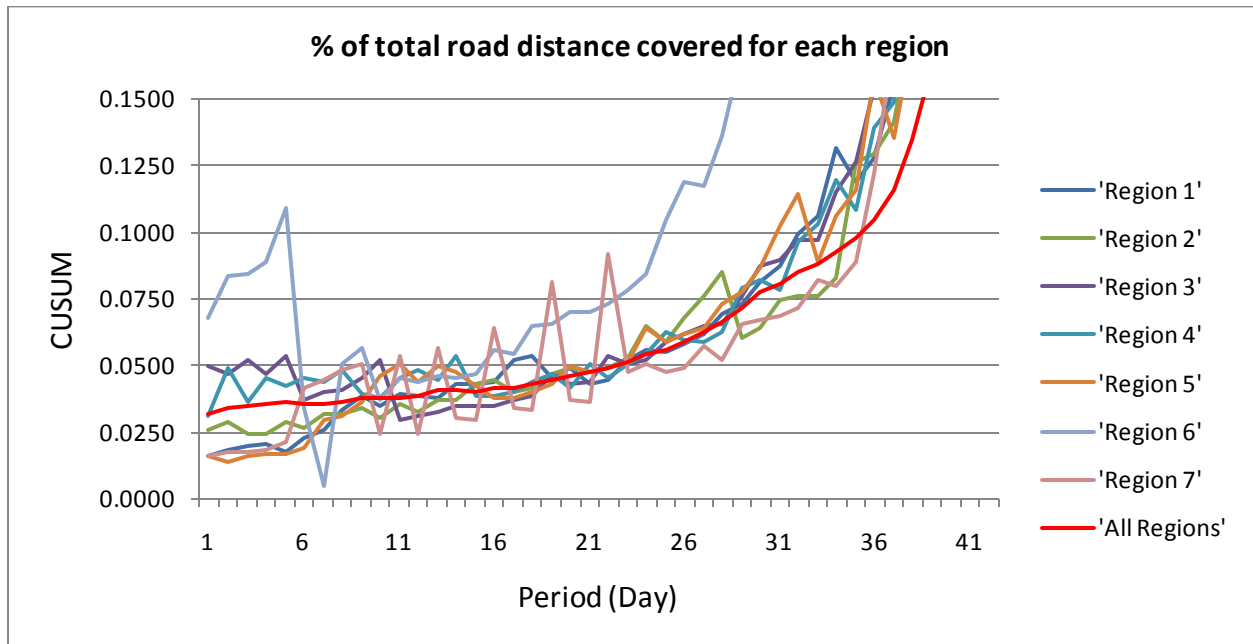
Figure 5.3 Percentage of Road Distance Covered for Each Region

5.8 Summary and Conclusions

Disaster related research has increased in recent years as a result of the number and cost of recent

disasters. However, as Altay and Green (2006) point out, relatively few studies have focused on

post-disaster recovery problems, such as disaster debris cleanup. Large volumes of disaster

debris pose a significant challenge to disaster coordinators who must decide how to best assign

resources across the disaster-affected area in order to collect and dispose of debris in the most

equitable, timely, and financially responsible way. This paper develops a self-balancing

CUSUM statistical process control approach to disaster cleanup. The approach is easy to use,

does not require accurate estimates of debris volumes, and provides DMCs with useful information for making real-time resource allocation decisions.

Using data from Hurricane Isabel in 2003, we demonstrate how the proposed self-balancing CUSUM approach may be used to assist DMCs with equitably allocating resources to support effective post-disaster debris cleanup operations. The results show that the proposed self-balancing approach can reduce not only the overall time to complete cleanup operations, but also the variability of time to complete operations between regions. Both of these factors are important in avoiding social, economic, and political unrest that often results because of ineffective post-disaster recovery operations.

5.9 Acknowledgements

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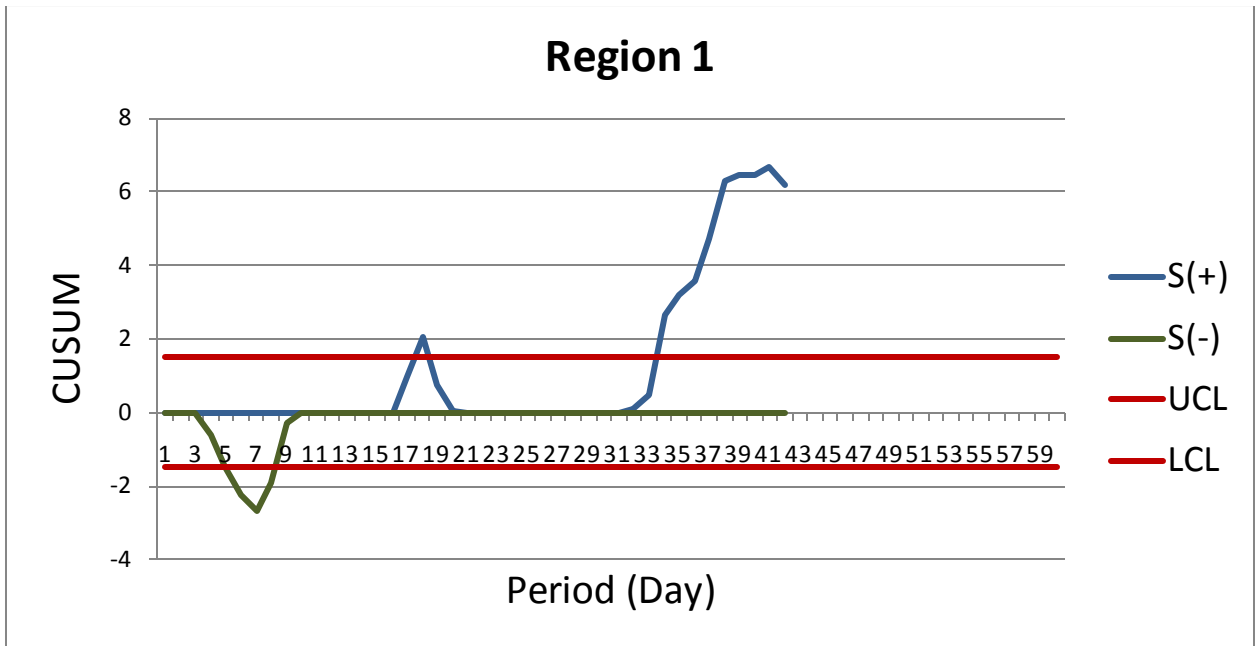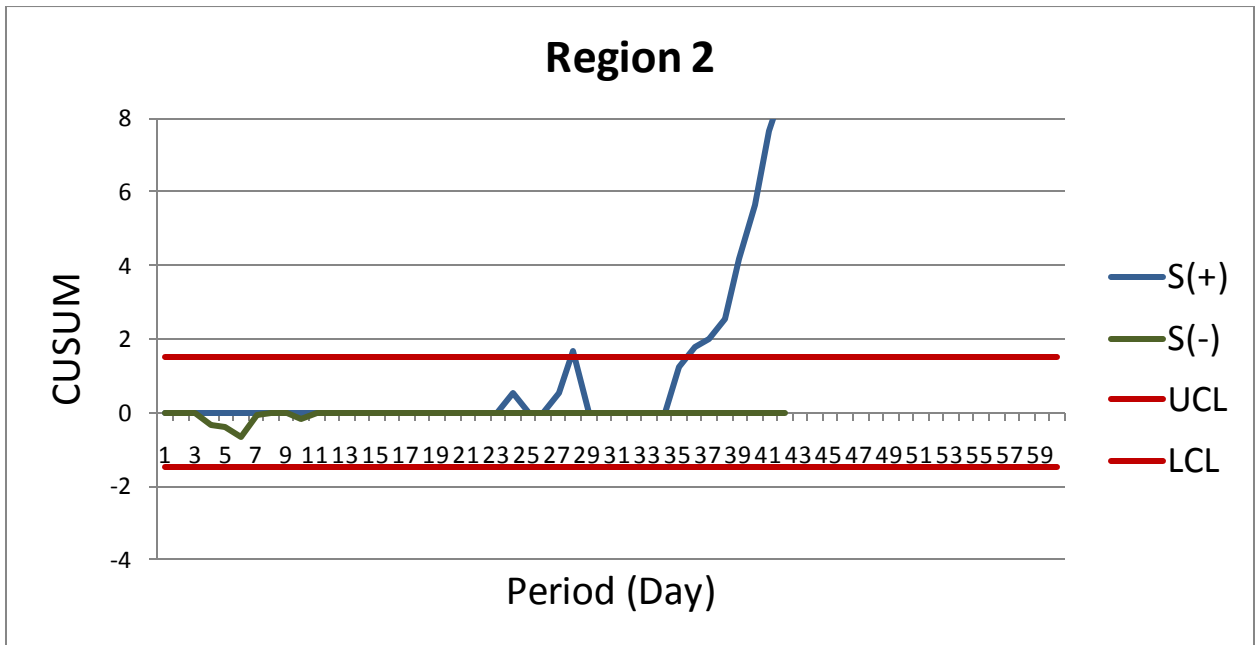
5.11 Appendix

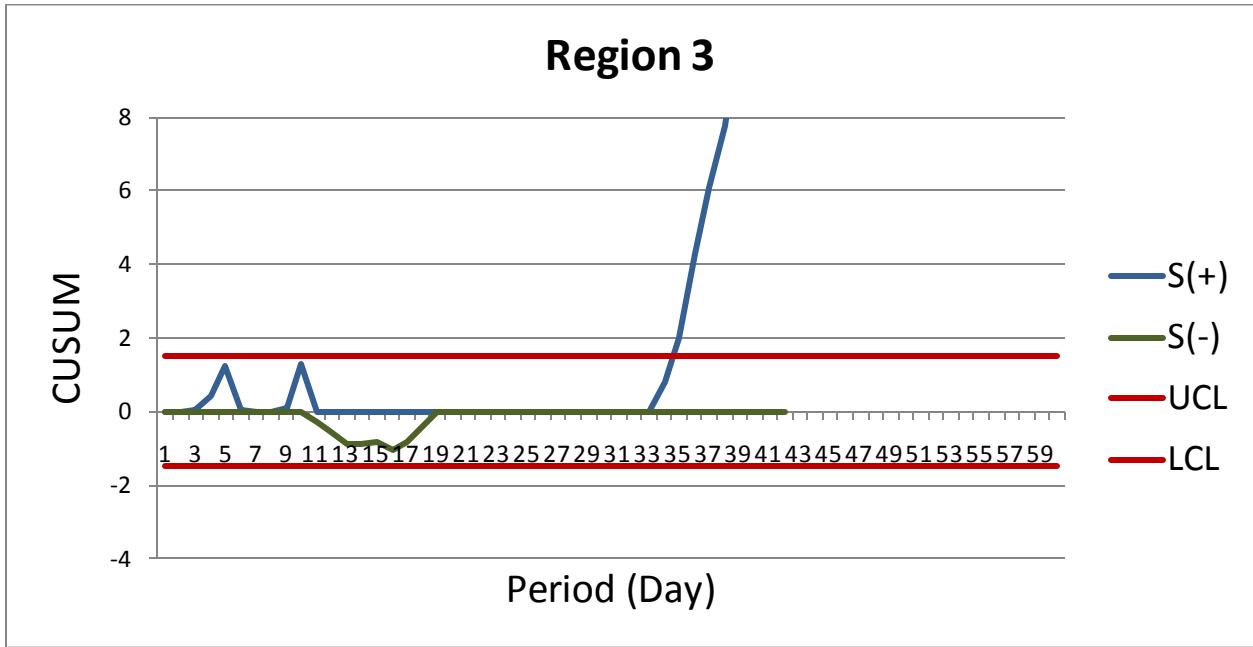**Figure 5.4 Region 1 CUSUM Chart**

Figure 5.5 Region 2 CUSUM Chart
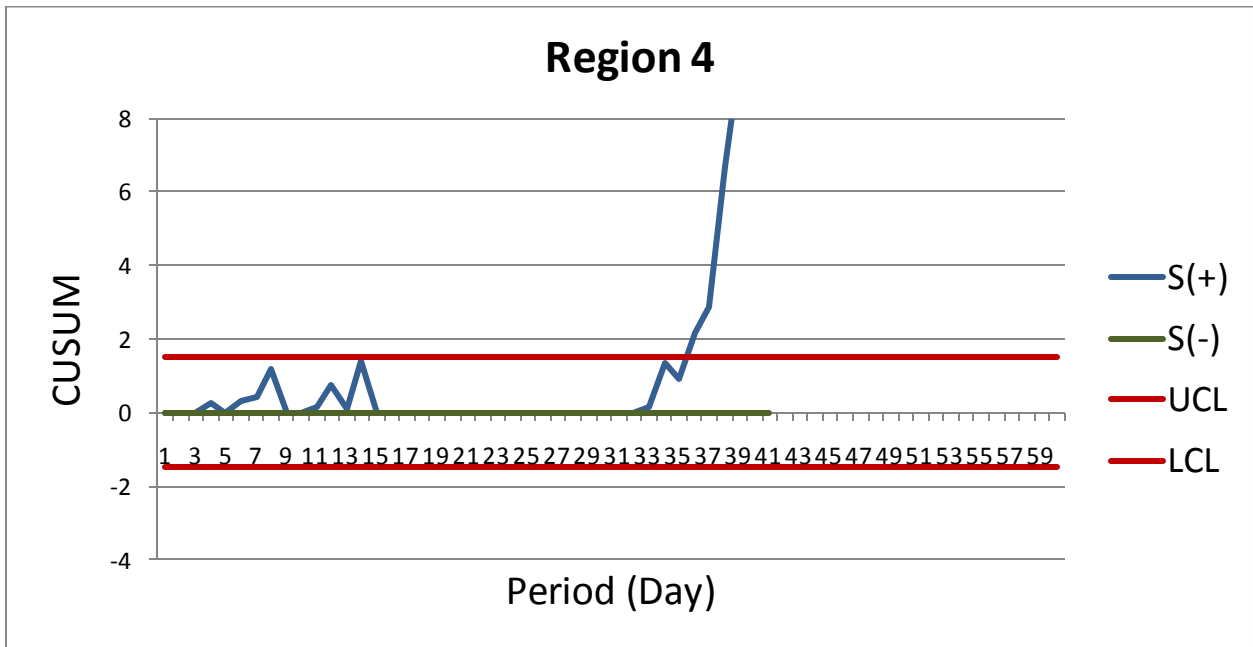
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Figure 5.6 Region 3 CUSUM Chart

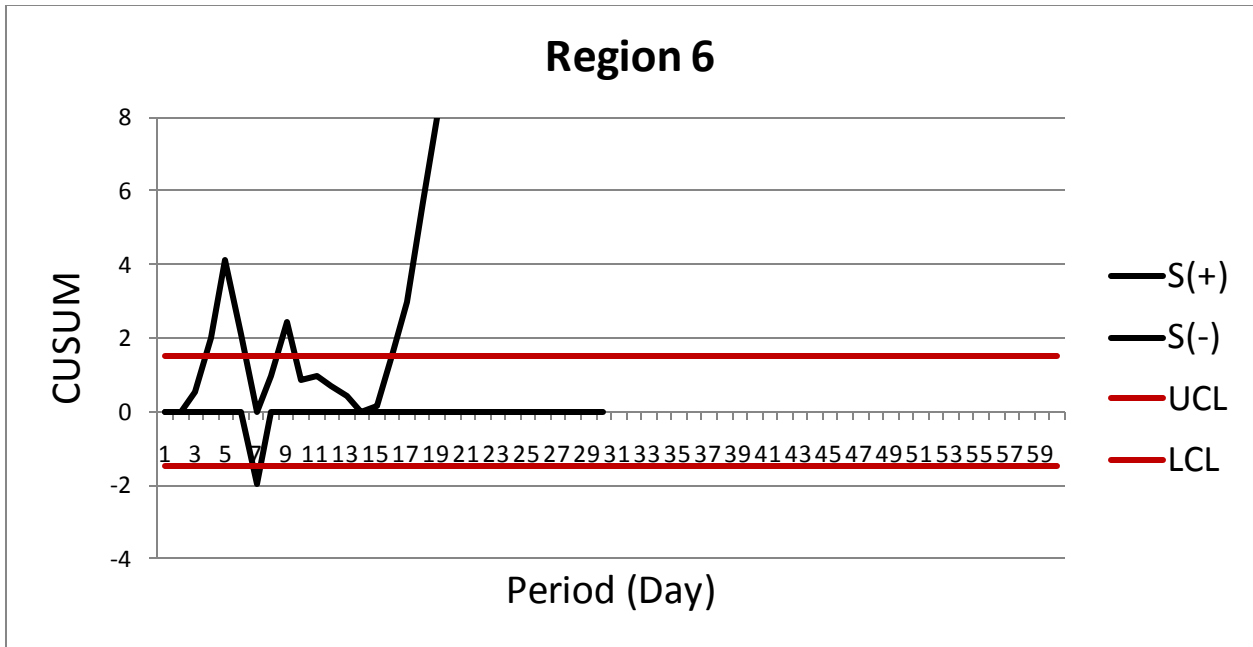**Figure 5.7 Region 4 CUSUM Chart**

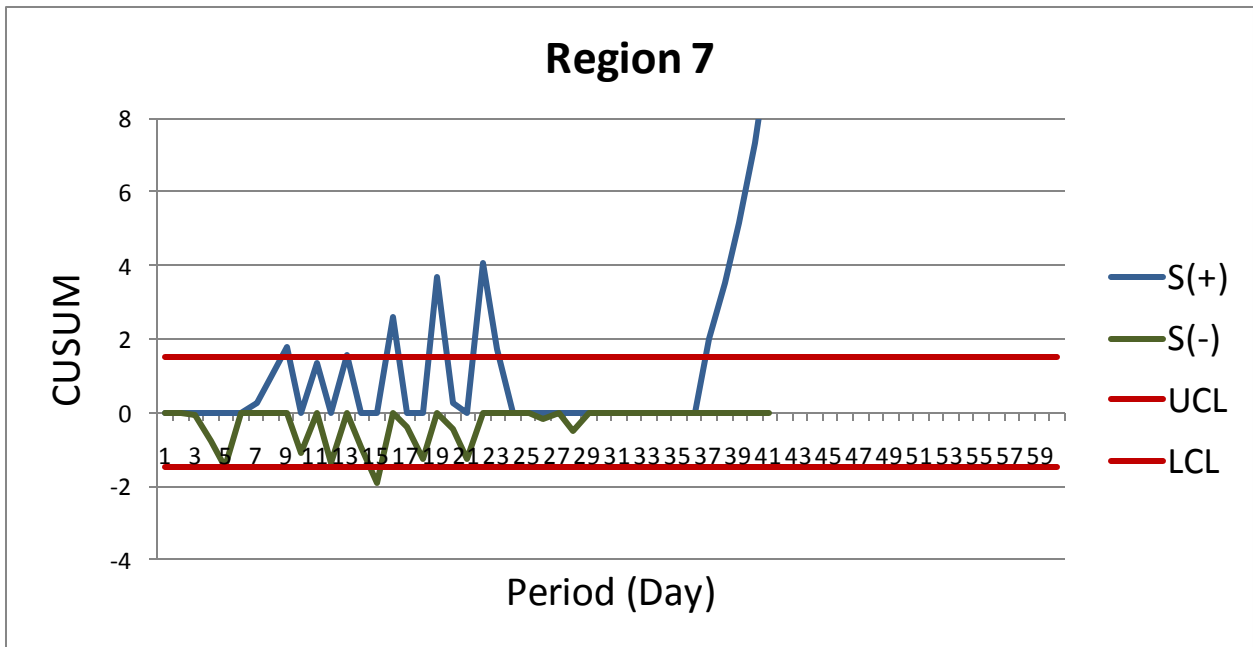**Figure 5.8 Region 6 CUSUM Chart**

Figure 5.9 Region 7 CUSUM Chart

Chapter 6

Summary and Conclusions

Hurricane Katrina and other recent disasters have created substantial interest in disaster management research. However, as Altay and Green (2006) point out, considerable emphasis has been given to pre-disaster planning and mitigation and to response activities such as evacuation, but relatively little attention has been given to studying post-disaster recovery activities, especially activities involving disaster debris cleanup. A few qualitative studies have highlighted the importance of and the need for effective management of debris cleanup following a disaster (Altay and Green 2006, Luther 2008, Roper 2008). However, we are unaware of quantitative research studies that develop models for assisting DMCs with strategic or operational aspects of disaster debris disposal operations.

The first manuscript of this dissertation research contributes a quantitative model for solving the TDSR Disaster Location Problem. First, the differences between disaster debris cleanup and everyday solid waste disposal are described, which underscore the need for additional research rather than relying on models developed for everyday solid-waste disposal. Second, a facility location model that incorporates the unique characteristics of disaster debris cleanup and FEMA's new recycling incentive policy is developed for the purpose of assisting disaster management decision makers with locating TDSR facilities. Using data recorded in 2003 from debris cleanup operations that occurred in Chesapeake, Virginia, after the landfall of Hurricane Isabel, three illustrative examples were developed for locating TDSR facilities. These examples highlighted unique aspects of disaster debris cleanup and the financial impact of FEMA's recent recycling policy upon the decision of where to locate TDSRs in support of cleanup operations. This study also underscores the benefits of considering primary and

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alternate TDSR assignments simultaneously and provides a model for debris planners to use in planning for debris cleanup operations.

A weighted-Tchebycheff goal program for solving the multiple objective Disaster Debris Contractor Assignment Problem (DDCAP) is developed in the second manuscript. The weighted-Tchebycheff goal programming formulation can be solved with standard software and is easy for DMs to understand and use—requiring only that they reflect their relative objective preferences by assigning weights to each objective. Again, using data from debris cleanup operations after Hurricane Isabel in 2003, it was shown that significant improvement in the balance of resource allocation, reduction in the overall duration, decreased transportation costs, and increased efficiency in contractor assignment can be obtained when considering the multiple objectives of the DDCAP simultaneously in the proposed weighted-Tchebycheff goal programming model.

Finally, in the third manuscript, a self-balancing CUSUM statistical process control chart approach to disaster cleanup is developed that is easy to use, does not require accurate estimates of debris volumes, and provides DMCs with useful information for making real-time resource allocation decisions. We demonstrate how the proposed self-balancing CUSUM approach may be used to assist DMCs with equitably allocating resources to support effective post-disaster debris cleanup operations. The results show that the proposed self-balancing approach can reduce not only the overall time to complete cleanup operations, but also the variability of time to complete operations between regions. Both of these factors are important in avoiding social, economic, and political unrest that often results because of ineffective post-disaster recovery operations.

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