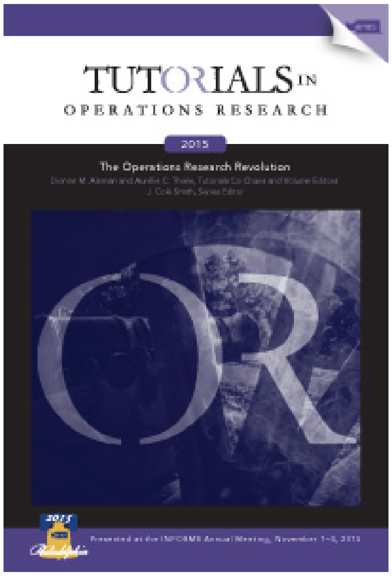

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Discrete Optimization Models for Homeland Security and Disaster Management

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Abstract Preparing for and responding to disasters, including acts of terrorism, is an important issue of national and international concern. Recent disasters underscore the need to manage disasters to minimize their impact on critical infrastructure and human suffering. In this tutorial, we survey the operations research literature that develops, analyzes, and applies discrete optimization models to effectively mitigate, prepare for, respond to, and recover from a wide variety of disasters.

Keywords tutorials in operations research; discrete optimization; integer programming; homeland security; emergency response; disasters; disaster mitigation; interdiction

1. Introduction

Preparing for and responding to disasters, including acts of terrorism, is an important issue of national and international concern. Recent national disasters such as the terrorist attacks on September 11, 2001, Hurricane Katrina in 2005, and Hurricane Sandy in 2012 as well as international catastrophes such as the 2004 Indian Ocean tsunami, the 2010 earthquake in Haiti, and the 2011 Tohoku earthquake and tsunami off the coast of Japan serve as reminders that we are vulnerable to disastrous and potentially catastrophic events.

Disaster management efforts such as mitigation, preparedness, response, and recovery are instrumental in minimizing negative consequences of severe events. Efforts to improve disaster management often involve managing limited resources, such as prelocating scarce resources and supplies, routing response vehicles, and scheduling recovery crews. As a result, discrete optimization models and algorithms are well suited to address many problems in disaster management. Doing so is extremely challenging as a result of informational uncertainties in terms of supply and demand, damage to critical infrastructure and transportation networks, limited resources, and challenges in communication between organizations providing aid and between those who need help. This INFORMS *TutORials in Operations Research* highlights the discrete optimization research that addresses these critical challenges.

This is an introductory tutorial rather than a comprehensive review, and as a result, only a few of the many research models under the umbrella of homeland security and disaster management are presented and discussed. For additional reading on these topics, we recommend the following surveys on security and disasters, including surveys on homeland security (Wright et al. [81]), aviation security (Lee et al. [43], McLay et al. [47]), critical infrastructure protection (Alderson et al. [3], Brown et al. [14]), disaster operations (Altay and Green [4]), interdependent systems (Ouyang [65]), and emergency logistics (Caunhye et al. [17]). We recommend Altay and Green [4] and Caunhye et al. [17] for those seeking a comprehensive review of operations research and management science research in disasters.

The rest of this INFORMS *TutORials in Operations Research* is organized as follows. First, we overview the types of disasters, the elements of disasters, and the federal agencies involved in managing disasters. Then we discuss information, data, and modeling approaches for disasters. Next, we highlight research involved in disaster mitigation, preparedness, response, and recovery. In each of these areas, we discuss one or two major streams of research that has emerged in the literature. Last, we end with some concluding thoughts.

2. Disasters Overview

In this section, we review several concepts and definitions that are relevant to research in security and disasters. Types of disasters differ in their magnitudes and scopes of physical and social impact. Although we use the term *disasters* generically in this paper to refer to intentional (man-made) and natural disasters with varying scopes of damage, we note that there are different scales associated with these events (Quarantelli [69]). Thresholds of disasters results in either emergencies, disasters, or catastrophes. Regardless of type, these events have a scope of impact at the community, region, and societal levels, not only at the individual level. Thus, research on emergency events such as health emergencies that are catastrophic only at the individual level are not included in this tutorial. Emergencies, disasters, and catastrophes are defined as follows.

Emergency. An event with local effects that can be managed at the local level, such as a bus accident or minor earthquake.

Disaster. A severe event that affects a region but whose damaging effects are not national in scope. The event can be managed with local, regional, and some national resources.

Catastrophe. A severe event that affects an entire nation and where the local and regional responses are inadequate or impossible because of affected critical infrastructure. The event threatens the welfare of a substantial number of people for an extended amount of time and therefore necessitates a national or international response. The Federal Emergency Management Agency (FEMA) expands upon this and defines a catastrophe as "any natural or manmade incident, including terrorism, that results in extraordinary levels of mass casualties, damage, or disruption severely affecting the population, infrastructure, environment, economy, national morale, and/or government functions" (U.S. Department of Homeland Security [79], p. 42).

There are a wide variety of events that could be characterized as disasters, and as a result, there are many government agencies that help manage disasters. In the United States, disaster management falls under the domain of the U.S. Department of Homeland Security (DHS). DHS has several departments and directorates that manage different hazards and disasters, including transportation security (Transportation Security Administration (TSA)), nuclear security (Domestic Nuclear Detection Office), border security (Customs and Border Protection (CBP)), maritime security (U.S. Coast Guard), and all natural hazards and disasters (FEMA) including hurricanes, earthquakes, floods, droughts, tornadoes, and wildfires. Additionally, military organizations such as the National Guard and the U.S. Coast Guard (the only military organization that is part of DHS) provide support during disasters. Disasters are not solely managed by government agencies. Numerous nongovernmental organizations (NGOs) are also involved in disasters and work cooperatively with government agencies. Beamon and Balcik [8] provide an overview of working with NGOs in disaster settings.

Managing disasters directly addresses the protection and recovery of *critical infrastructure* in addition to critical human needs such as loss of life and morbidity. It is worth defining critical infrastructure and noting that critical infrastructure does not need to be *physical* infrastructure. The USA Patriot Act[1] defines critical infrastructure as

> ...systems and assets, whether physical or virtual, so vital to the United States that the incapacity or destruction of such systems and assets would have a debilitating impact on security, national economic security, national public health or safety, or any combination of those matters.

[1] Also known as the Uniting and Strengthening America by Providing Appropriate Tools Required to Intercept and Obstruct Terrorism Act of 2001 (Public Law 107-56, 107th Congress (October 26, 2001)).

Protection from disasters involves strengthening several critical elements across the disaster life cycle. We use the hazards and disasters areas from the National Academy of Engineering (NAE) (National Research Council [60]) to subdivide the disaster life cycle into these components:

- *Vulnerability* is the potential for physical harm and social disruption. Physical harm represents the damage and threat of damage to physical infrastructures and the natural environment. Social disruption and vulnerability represent threats to human populations, such as death, injury, morbidity, and disruption to behavior and social functioning.
- *Mitigation* includes actions taken prior to a disaster to prevent or reduce the potential for harm, physical vulnerability, and social disruption. Mitigation can be *structural*, which involves designing, constructing, maintaining, and renovating physical infrastructure to withstand the impact of a disaster, or *nonstructural*, which involves reducing exposure of human populations and physical infrastructure to hazard conditions.
- *Preparedness* includes actions taken prior to a disaster to aid in the response and recovery during and after a disaster. Preparedness actions often include the development of formal disaster plans and the maintenance of resources that are used in response and recovery.
- *Emergency response* includes actions during and after a disaster to protect and maintain systems, rescue and respond to casualties and survivors, and restore essential public services.
- *Recovery* includes efforts to reestablish pre-disaster systems and services through the restoration and repair of infrastructure and social and economic routines, such as education, consumption, and healthcare.

The NAE notes that classification schemes are based on various characteristics of disasters, such as their length of forewarning, detectability, speed of onset, magnitude, scope, and duration of impact. Additionally, the NAE report (National Research Council [60]) recommends that willful acts of terrorism be included in this life cycle.

Discrete optimization has been applied to problems across the disaster life cycle. This INFORMS *TutORials in Operations Research* focuses on the latter four areas where discrete optimization has had the most impact. The following list includes several examples of the types of problems that have been addressed.

- Mitigation
  - Checkpoint screening for security
  - Network design and fortification
  - Prelocating medical facilities and response stations
- Preparedness
  - Prepositioning crews and supplies in advance of a disaster
  - Evacuation planning
  - Emergency crew scheduling
- Emergency response
  - Urban search and rescue
  - Routing and distribution of supplies and commodities
  - Hospital evacuation
- Recovery
  - Debris cleanup and removal
  - Road, bridge, and facility repair and restoration
  - Replanting and restoration of forests and wetlands affected by a natural disaster

See Altay and Green [4] for more examples. The NAE definitions served as a guide for how we classified research models into these areas. Before introducing the research models, we first discuss issues pertinent to initiating a research project in security and disasters.

3. Data, Information, and Modeling Challenges

The nature of disasters poses several challenges for research that involve both modeling and data collection. These challenges exist across all components of the disaster life cycle. In this section, we summarize some of these challenges and differentiate discrete optimization modeling approaches in a disaster setting from those in more traditional (non-disaster) settings.

First, disasters applications motivate new criteria that are reflected in discrete optimization objective functions and modeling choices. In disasters, there is a focus on critical needs such as loss of life and morbidity compared with criteria in traditional models that often reflect quality and profit. Models for disasters often reflect systems whose performance over time is the main criterion. As a result, model objectives may reflect the delivery of critical time-sensitive commodities instead of cost or distance traveled (Campbell et al. [16]). Many disasters models reflect a coverage objective function to evaluate acceptability of service. Coverage is used in many traditional models. However, coverage may be modeled in different ways for disaster applications to capture, for example, different types of coverage necessary for the emergency at hand or backup coverage if availability of service is a concern (Jia et al. [38]).

Discrete optimization models for disasters are not merely traditional discrete optimization models with new objective functions. Disasters motivate new structural components of the models that arise from several mechanisms. We list three of these mechanisms of many that exist. First, several agencies often work together to respond to and deliver commodities after a disaster, which introduces multiple decision makers or new model features that reflect limited control over certain parts of the operations. Second, issues such as fairness often emerge in models for disasters. Equity can be modeled in many different ways in a discrete optimization model (Leclerc et al. [41]). Third, traditional models often implicitly assume the network components are reliable, which may not be valid during disasters when, for example, facilities are damaged and may not be fully operational.

Other issues affect model choices and model structure. Models for disasters almost always focus on events with high consequences, and there is often an interest in vulnerability, worst-case performance, and events that overwhelm the resources and capacities in the system. The focus on vulnerability can be incorporated into the models in several ways. One way is to optimize over the worst-case scenario as in max-min models and network interdiction models (Alderson et al. [3]). Another way to model vulnerability is through the inclusion of uncertain and unpredictable demands and system failures. Disaster models consider cascading failures in a system, not independent component failures as considered in the reliability literature. Cascading failures could be seen in how demands are modeled, such as characterizing demands that arise from different types of emergencies (e.g., a dirty bomb attack near a seaport) (Jia et al. [38]) or in network damage that occurs across the network (McLay et al. [51]). Information about the emergencies and the operability of interdependent systems (e.g., communication and power) is often inaccurate and unavailable, leading to decision making under uncertainty. See Beamon and Balcik [8] and Campbell et al. [16] for a discussion of the issues salient to disaster and logistics.

The ultimate goal of most discrete optimization models in the literature is to understand how to use scarce resources. In a disaster setting, resources may include new resources specific to the disaster at hand—such as anthrax vaccines dispensed after an anthrax attack—or resources used for non-disaster scenarios that may be used in new ways during disaster management—such as ambulances that evacuate hospital patients after a hurricane. Similarly, there are different resource deployment strategies prior to and during disaster events, such as proactively deploying medical supplies in anticipation of an emergency or a reactive deployment of first responders after a large-scale emergency. These resource deployment strategies may differ from those used for routine operations, and therefore, new models are needed for exploring new deployment strategies.

Data collection is a critical component of the research process. Data used for disasters models can be extremely difficult to obtain. This is true for many application areas, but it is particularly true for disasters applications. Data may be impractical to collect in homeland security events, where, for example, terrorists goals and decision processes may be unknowable and terrorist attacks are rare events. When data can be collected, there may not be a system in place to collect the data needed after a disaster (e.g., the number of evacuees in shelters). Additionally, data may be perishable and therefore must be collected in a timely manner (National Research Council [60]). For this reason, agencies such as the National Science Foundation and the National Hazards Center at the University of Colorado at Boulder offer research grants for traveling to an area affected by a disaster and collecting data before the data perish.

Data that are collected may be inaccurate and incomplete. For example, an emergency medical service may record demand from 911 call logs. If there are communications failures after a hurricane strikes and patients cannot call for service, they may instead drive to a fire station for service. These patients may not be entered into call logs. Finally, typical commercial computer-aided dispatch software used by 911 centers do not have codes for large-scale emergencies, such as carbon monoxide poisoning caused by generators used during power outages. Instead, these 911 calls are mapped to codes used for typical emergencies (e.g., overdose). As a result, it may be impossible to accurately count and characterize demand that occurs during a disaster event.

Finally, we note that data can be used in conjunction with the models in several ways. Data can be used in a static manner, where they are collected and used to parameterize the models that are solved ahead of time. Models that address response and recovery may include real-time decision making and may integrate data from multiple sources (variety) that arrive in real time (velocity). These "big data" issues of variety and velocity are particularly challenging and are at present a national research priority.

The next four sections introduce several research models across components of the disaster life cycle introduced in §2.

4. Disaster Mitigation

Disaster mitigation focuses on preventing a disaster or reducing the harmful effects of a disaster. There are many ways in which discrete optimization models can assist with mitigating the effects of disasters by taking actions prior to a disaster. We focus on two classes of models for disaster mitigation: (1) screening and prescreening problems in homeland security applications that seek to reduce harm through detection and prevention and (2) network interdiction models that focus on identifying network vulnerabilities and fortifying critical network components. Other models address hazardous material transportation (Erkut and Ingolfsson [24], Sherali et al. [75]) and mitigation efforts for a wide range of disasters (Altay and Green [4]).

4.1. Screening and Detection

There are many papers that use discrete optimization models for risk-based screening in homeland security applications, where applications include passenger screening for aviation security and cargo screening for nuclear security. The work presented here focuses on aviation security (both checked baggage screening and passenger screening) and screening cargo containers for nuclear material that can be weaponized.

4.1.1. Checked Baggage Security. Early research in applying discrete optimization models to allocate scarce aviation security resources dates back before September 11, 2001 and grew out of research collaborations with the Federal Aviation Administration (FAA), which was (then) the federal agency in charge of aviation security. The goal was how to optimally deploy and use limited baggage screening devices. At that time, the FAA performed a risk assessment on each passenger, and those who could not be cleared of posing a risk were labeled *selectees*, and the checked baggage of these passengers was prioritized for screening. The remaining passengers were labeled *non-selectees*; the checked baggage of non-selectees did not undergo screening.

A stream of papers identifies performance measures for screening selectee baggage and examine how to allocate scarce screening resources to stations (Jacobson et al. [33]). A station is a set of airport facilities that share security resources. There may be several stations in a large hub airport. Jacobson et al. [36] propose three performance measures for assessing the effectiveness of security device deployments for screening selectee checked baggage across a set of flights. Note that a flight segment is the flight between the takeoff and landing of an aircraft from one airport to another. A flight segment is *uncovered* if one or more selectee bags on the flight has not been screened, whereas a flight segment is *covered* if all selectee bags on it have been screened. The performance measures are

1. uncovered flight segments (UFS), which captures the total number of uncovered flights;
2. uncovered passenger segments (UPS), which captures the total number of passengers on uncovered flights; and
3. uncovered baggage segments (UBS), which captures the total number of unscreened selectee bags (regardless of flight).

Jacobson et al. [36] propose three models for identifying how to allocate resources according to these three performance measures. The model parameters include

- $F = \{f_1, f_2, \ldots, f_n\}$ = a set of n flights,
- $C(f_i)$ = the number of selectee bags on flight f_i, $i = 1, 2, \ldots, n$,
- $N(f_i)$ = the number of passengers on flight f_i, $i = 1, 2, \ldots, n$, and
- S = the upper bound on the number of bags that can be screened.

The Uncovered Passenger Segment Problem (*UPSP*). Find a subset of flights $F' \in F$ such that $\sum_{f_i' \in F'} C(f_i') \leq S$, and $\sum_{f_i' \in F'} N(f_i')$ is maximized.

The Uncovered Flight Segment Problem (*UFSP*). Find a subset of flights $F' \in F$ such that $\sum_{f_i' \in F'} C(f_i') \leq S$, and the number of flights $|F'|$ is maximized.

The Uncovered Baggage Segment Problem (*UBSP*). Find a subset of flights $F' \in F$ such that $\sum_{f_i' \in F'} C(f_i') \leq S$, and $\sum_{f_i' \in F'} C(f_i')$ is maximized.

Jacobson et al. [36] find that deploying security devices according to the UFS and UPS performance measures results in different types of solutions (screening more, smaller flights as opposed to fewer, larger flights). However, they note that it is sometimes possible to simultaneously improve both UFS and UPS performance measures.

These three models were extended in several ways to consider other issues when screening selectee baggage. Jacobson et al. [34] formulate problems that model multiple sets of flights originating from multiple stations subject to a finite number of security resources. The additional model parameters include

- m = the number of screening stations, and
- $F_i \subset F$ = the set of flights that are associated with station $i = 1, 2, \ldots, m$, where $F_1, F_2, \ldots, F_m$ are a partition of F.

Jacobson et al. [34] introduce six optimization models that allocate the screening capacity S to stations according to the three performance measures. The first set of three models considers general allocation sizes, and the second set of models considers preallocated sizes. For brevity, we only present the two discrete optimization models associated with the UPS measure.

The Multiple Station Passenger Segment Security Allocation and Screening Problem with General Allocation Sizes. Find the subsets of flights $F_i' \subset F_i$, $i = 1, 2, \ldots, m$ and a set of baggage screening security device capacity allocations S_i, $i = 1, 2, \ldots, m$ that maximizes $\sum_{i=1}^{m} \sum_{f_i' \in F_i'} N(f_i')$ such that $\sum_{i=1}^{m} S_i \leq S$ and $\sum_{f_i' \in F_i'} C(f_i') \leq S_i$, $i = 1, 2, \ldots, m$.

The second model considers predetermined allocation sizes, since using security devices requires capacity to be assigned to stations in fixed, discrete amounts. The second model adds two sets of parameters:

- $A = \{a_1, a_2, \ldots, a_l\}$ = the set of available security device allocations, and
- $W(a_j)$ = the capacity associated with security device allocation a_j, $j = 1, 2, \ldots, l$.

The resulting discrete optimization model seeks to assign devices to stations and selects the flights to screen with these allocations.

The Multiple Station Passenger Segment Security Allocation and Screening Problem with Predetermined Allocation Sizes. Find the subsets of flights $F'_i \subset F_i$, $i = 1, 2, \ldots, m$ and a partition $\{A'_i, A'_2, \ldots, A'_m\}$ of security device allocations A to stations that maximizes $\sum_{i=1}^{m} \sum_{f'_i \in F'_i} N(f'_i)$ such that $\sum_{i=1}^{m} \sum_{f'_i \in F'_i} C(f'_i) \le \sum_{a'_j \in A'} W(a'_j)$.

Jacobson et al. [35] and Virta et al. [80] extend the ideas introduced thus far to consider the impact of originating and transferring passengers on the effectiveness of baggage screening security systems, since a selectee bag screened at its point of origin is covered for two flight segments as opposed to one flight segment for selectee bags screened while transferring.

McLay et al. [52] build on this framework by extending the performance measures for attacks with conventional weapons to attacks with weapons of mass destruction (WMD) since the scope of damage may extend beyond that of the aircraft and its passengers. In particular, they consider screening for a nuclear weapon in checked baggage on international flights. This paper adds a fourth coverage performance measure to the list from above; this measure considers covering targets (modeled as destination airports) and evaluates the trade-offs between the performance measures. Covering targets becomes an important operational goal in addition to device utilization since it is a proxy for minimizing the consequences associated with an attack using WMDs that could have extensive damage beyond that of the airplane:

4. uncovered targets (UT), which captures the total number of uncovered targets (e.g., destination cities) where a target is covered if all flights to the target are covered.

McLay et al. [52] propose goal programming models that balance the UT measure with the UPS, UFS, and UBS measures.

The models in this section focus on coverage models for screening checked baggage. Next, we introduce risk-based models that generalize the binary coverage paradigm.

4.1.2. Passenger Screening. Another set of papers applies discrete optimization, integer programming, and Markov decision process methodologies for analyzing risk-based passenger screening systems in aviation security by considering multilevel passenger screening strategies. *Multilevel screening* considers two or more levels of security to screen passengers, which generalizes the binary system introduced earlier (i.e., selectees and non-selectees) that was used in the coverage models. This stream of literature contains papers that address *static screening* (where passenger screening decisions are made up front for many passengers at the same time) and *dynamic screening* (where passenger screening decisions are made in real time). All of these models have been instrumental in improving screening operations at airports in the United States. The research provided in these papers provides the critical analysis that is at the foundation of security operations at commercial airports throughout the United States, including the fundamental technical analysis that laid the basis for risk-based security, which in turn led to the TSA PreCheck program.

McLay et al. [53] introduce a framework for multilevel passenger screening using discrete optimization methodologies and algorithms for static screening. In their framework, each passenger must be assigned to a *class* that corresponds to a set of procedures using security screening devices and personnel. Each class $i = 1, \ldots, M$ is defined by a security level L_i, a fixed cost associated with device purchase and installation costs FC_i, and a marginal cost associated with passenger inspection costs MC_i. The model maximizes a security measure subject to a budget constraint.

The parameters are as follows:

- $N =$ the number of passengers;
- $M =$ the number of screening classes;
- $\mathrm{AT}_j =$ the assessed threat value of passenger $j = 1, \ldots, N$, a risk assessment of passenger j returned by a passenger prescreening system;
- $L_i =$ the security level achieved by screening a passenger with screening class $i = 1, \ldots, M$;
- $\mathrm{FC}_i =$ the fixed cost associated with screening class $i = 1, \ldots, M$;
- $\mathrm{MC}_i =$ the marginal cost of screening a passenger with screening class $i = 1, \ldots, M$; and
- $B =$ the screening budget to be used for the time horizon.

The decision variables are as follows:

- $y_i = 1$ if screening class i is used and 0 otherwise, $i = 1, 2, \ldots, M$; and
- $x_{ij} = 1$ if passenger j is screened by class i and 0 otherwise, $i = 1, 2, \ldots, M$, $j = 1, 2, \ldots, N$.

The model is formulated as an integer programming model:

$$\max \quad \left\{ \sum_{i=1}^{M} \sum_{j=1}^{N} L_i \, \mathrm{AT}_j \, x_{ij} \right\} \tag{1}$$

$$\text{subject to} \quad \sum_{i=1}^{M} \sum_{j=1}^{N} \mathrm{MC}_i \, x_{ij} + \sum_{i=1}^{M} \mathrm{FC}_i \, y_i \le B, \tag{2}$$

$$\sum_{i=1}^{M} x_{ij} = 1, \quad j = 1, 2, \ldots, N, \tag{3}$$

$$x_{ij} - y_i \le 0, \quad j = 1, 2, \ldots, N, \; i = 1, 2, \ldots, M, \tag{4}$$

$$y_i \in \{0, 1\}, \quad i = 1, 2, \ldots, M, \tag{5}$$

$$x_{ij} \in \{0, 1\}, \quad i = 1, 2, \ldots, M, \; j = 1, 2, \ldots, N. \tag{6}$$

This model assigns N passengers to one of M classes. The objective (1) is to maximize the total security, which is represented by the sum of the product of the passenger assessed threat values and their associated screening class security levels ($\sum_{i=1}^{M} \sum_{j=1}^{N} L_i \, \mathrm{AT}_j \, x_{ij}$). The first constraint (2) is the screening budget knapsack constraint. The second set of constraints (3) ensures that all passengers undergo screening. The third set of constraints (4) links the passenger screening assignment variables to the class usage variables. The final two sets of constraints ensure that the variables are binary. A solution to the model yields a set of passenger assignments to classes. One of the insights is that passengers tend to be assigned to few classes, with expedited screening of the lower-risk passengers.

Several other papers formulate models for static passenger screening. McLay et al. [54] formulate a second multilevel screening model that considers how to optimally use security devices once they are in place by focusing on the devices in use that may be shared across security classes. Lazar Babu et al. [40] investigate the possible benefit from using multiple classes for screening passengers using linear programming models. They evaluate the false alarm rate, since false alarms are a proxy for passenger inconvenience. They find that risk-based security using multiple classes is beneficial, even when a prescreening system is not used to differentiate passenger risk. Nie et al. [61] extend this model to examine the trade-offs between two performance measures: the probability of a false alarm and the total number of screeners needed. Nearly all research models assume that each security device or checkpoint yields a binary response, either alarm or clear. By contrast, Nie et al. [61] use checkpoint screening outcomes to sequentially “score” passengers and group passengers according to their scores. All of these models support the effort to screen passengers in a risk-based manner.

The models by Lazar Babu et al. [40], McLay et al. [53, 54], and Nie et al. [61] are static, meaning that they make passenger screening decisions for many passengers at the same time.

In these models, the set of passengers to be screened at a particular station in an airport in a given period of time is assumed to be known, and hence, passenger risk levels are assumed to be known a priori.

A number of models for *dynamic* passenger screening provides insight into real-time screening decisions. Dynamic passenger screening is modeled in the literature as a *sequential* process, where each passenger's risk level becomes known upon arrival to a security checkpoint. Several papers propose Markov decision process models for identifying dynamic passenger screening policies. McLay et al. [55] introduce a sequential stochastic passenger screening model that determines how to optimally assign passengers (in real time) to aviation security resources. They use a binary paradigm where passengers are classified as either selectees or non-selectees. The model uses the passengers' perceived risk levels to identify an optimal policy that maximizes the expected number of true alarms, subject to capacity and assignment constraints. McLay et al. [56] extend this model to consider the impact of multilevel screening and present a heuristic to provide approximate solutions. Nikolaev et al. [62] propose a two-stage model for sequential multilevel passenger screening problems. The first stage considers the screening system design problem, i.e., which security devices to purchase, whereas the second stage determines real-time passenger screening assignments. Their model is transformed into a deterministic integer program rather than modeled using a Markov decision process.

4.1.3. Cargo Screening. Border security has emerged as a critically important yet vulnerable component in the homeland security system, since it has the potential to prevent illicit material and weapons used for launching terrorist attacks from entering the United States. Ninety-five percent of international goods that enter the United States come through one of the ports of entry, most of which enter the United States on cargo containers (Fritelli [26]). Therefore, screening cargo entering the United States for nuclear material is an important component of border and nuclear security.

Early screening was performed by physically unpacking cargo containers and inspecting their contents. Given the expense associated with inspection, few containers were unpacked and inspected. Additionally, there was an effort to develop more effective screening methods based on imaging or passive radiation detection to efficiently screen more containers. However, technologies for detecting nuclear and radiological material have lagged behind their need. At present, nearly all cargo containers are screened by radiation portal monitors and other technologies (Bakır [6]). More advanced screening and inspection technologies, such as imaging and physical inspection, are used more sparingly and are targeted at high-risk containers (U.S. Customs and Border Protection [78]).

A prescreening system called the Automated Targeting System is used to perform a risk assessment on cargo containers that can aid in designing risk-based screening systems. A risk-based approach to cargo screening is part of the CBPs plan for security; however, few guidelines are given to implement and assess such a strategy. A stream of literature focuses on how to screen these cargo devices in a risk-based environment.

McLay et al. [57] provide a linear programming model to examine how to perform *primary screening* on cargo containers exiting a security checkpoint, where prescreening classifies each cargo container as high risk or low risk. When a cargo container enters a security station, it undergoes screening by several *sensors*, each of which yields an alarm or clear response. Based on this total number of sensor alarms, a system response is given (Kobza and Jacobson [39]). Either the system response clears the cargo container (and it exits the security station) or it undergoes *secondary screening*. It is worth noting that the screening checks can be performed over time across multiple checkpoints during a container's journey, culminating in a single system response decision at a U.S. port security checkpoint. McLay and Dreiding [48] extend this base model to consider multiple prescreening risk groups. These risk-based models give insight into how many alarms must sound before a cargo container should undergo secondary screening.

The base model can also be extended to study the efficacy of primary and secondary screening as well as the type—not just the number—of primary security alarms. Dreiding and McLay [23] propose the following model to assign prescreened cargo containers to primary screening groups and identify the mix of primary screening outcomes that warrant secondary screening based on risk assessments. All containers undergo primary screening (determined by the model), which yields a set of outcomes (e.g., the combination of devices that alarm or clear). A container may undergo secondary screening (i.e., inspection), which is determined by the model and depends on the containers' prescreening group, primary screening procedures, and primary screening outcomes. The model determines how to define primary and secondary screening alarms using a prescreening-based approach given a total screening budget.

Several other papers examine risk-based cargo container screening. Boros et al. [13] develop a large-scale linear programming model to sequence screening tests for screening cargo containers. Boros et al. [12] expand on this work to identify screening policies using decision trees and knapsack problem models solved using dynamic programming algorithms. Ramirez-Marquez [70] uses decision trees to find order-dependent cargo container inspection strategies that minimize inspection costs. Gaukler et al. [28, 27] investigate how to improve prescreening by supplementing risk assessments with radiography-based images to identify potential containerized threat scenarios, and they propose hybrid screening systems and container-specific false alarm rates. All of these models support risk-based screening methods for determining how to efficiently and effectively use limited screening resources.

4.2. Network Design and Fortification

Network models are prevalent in disasters and security models, and they address the need to design and fortify parts of a network to mitigate vulnerabilities. Network interdiction models focus on worst-case failures, where the failures could be due to natural or intentional causes such as natural disasters, terrorism, and catastrophic accidents as opposed to random component failure or reliability. We refer the reader to survey papers by Smith [76] and Morton [59] for more information on network interdiction.

Nearly all network interdiction problems in the homeland security literature are modeled as Stackelberg games, where the leader acts first by interdicting components of the network (e.g., lengthening arcs) and the follower acts second by performing recourse actions (e.g., selecting a shortest path from the source to the sink). There are several classes of network interdiction models that are well studied in the literature, including

- shortest-path network interdiction, where the operator seeks to find the shortest path from a source to a sink after the leader lengthens arcs in the network;
- maximum reliability network interdiction, where the operator seeks to maximize the probability of evading detection after the leader reduces the evasion probability on some of the arcs in the network;
- maximum flow interdiction, where the operator seeks to maximize the flow achievable on the network after the leader reduces some of the arc capacities; and
- p-median network interdiction, where the operator seeks to minimize the total worst-case distance from the customers to the nearest facility after the leader removes some of the facilities.

Facility location network models play a critical role in emergency preparedness and response, and therefore, the vulnerability of facility location network models is important for understanding resilience. Early models such as the maximal covering location problem (Church and ReVelle [19]) have been widely used to locate fire engines and ambulances for responding to routine emergencies. This basic location model is the foundation of many additional models for located public service resources (e.g., Ansari et al. [5], Batta et al. [7], Daskin [22], Erkut et al. [25], McLay [46]) that consider facility unavailability akin to reliability.

More recently, several papers extend these ideas to consider worst-case facility unavailability as a result of interdiction. There is a growing stream of literature in the area of facility location interdiction that supports disaster mitigation efforts. Church et al. [20] introduce the r-interdiction median problem and the r-interdiction covering problem to study network performance when r facilities are interdicted. Their models use the following parameters:

- $F =$ the set of existing facilities;
- $I =$ the set of demand locations;
- $a_i =$ demand at location $i \in I$;
- $d_{ij} =$ the shortest distance between i and j, $i \in I$, $j \in F$;
- $r =$ the number of facilities to be interdicted or eliminated;
- $T_{ij} = \{k \in K \mid k \neq j \text{ and } d_{ik} > d_{ij}\} =$ the set of existing sites (not including j) that are as far or farther than j is from demand i; and
- $N_i \subset F =$ the set of facility sites that cover demand i, $i \in I$.

The r-interdiction median problem admits the following decision variables:

$$s_j = \begin{cases} 1 & \text{if facility } j \text{ is eliminated, } j \in F, \\ 0 & \text{otherwise;} \end{cases}$$

$$x_{ij} = \begin{cases} 1 & \text{if demand } i \text{ is assigned to a facility at } j,\ i \in I,\ j \in F, \\ 0 & \text{otherwise.} \end{cases}$$

The r-interdiction median problem is formulated as an integer programming model:

$$\begin{aligned} z = \max \quad & \left\{ \sum_{i \in I} \sum_{j \in F} a_i d_{ij} x_{ij} \right\} && (7) \\ \text{subject to} \quad & \sum_{j \in F} s_j = r, && (8) \\ & \sum_{j \in F} x_{ij} = 1, \quad i \in I, && (9) \\ & \sum_{k \in T_{ij}} x_{ik} \leq s_j, \quad j \in F, && (10) \\ & x_{ij} \in \{0, 1\}, \quad i \in I, j \in F, && (11) \\ & s_j \in \{0, 1\}, \quad j \in F. && (12) \end{aligned}$$

The objective function (7) seeks to maximize the resulting total weighted distance between demand locations and facilities that have not been interdicted. The first constraint (8) requires that r facilities are interdicted. The second set of constraints (9) assigns each demand location to a facility after interdiction. The third set of constraints (10) prevents assignments to facilities farther than the closest facility after interdiction. The final two sets of constraints establishes integer restrictions on the variables.

The r-interdiction covering problem is similar to the r-interdiction median problem except that a demand location is no longer covered if all of the facilities that cover the location have been interdicted. The r-interdiction covering problem admits the following decision variables in addition to s_j, $j \in J$:

$$y_i = \begin{cases} 1 & \text{if demand } i \text{ is no longer covered,} \\ 0 & \text{otherwise;} \end{cases}$$

$$\begin{aligned} z = \max \quad & \left\{ \sum_{i \in I} a_i y_i \right\} && (13) \\ \text{subject to} \quad & \sum_{j \in F} s_j = r, && (14) \end{aligned}$$

$$y_i \le s_j, \quad i \in I, j \in N_i \cap F, \tag{15}$$
$$y_i \in \{0,1\}, \quad i \in I, \tag{16}$$
$$s_j \in \{0,1\}, \quad j \in F. \tag{17}$$

The objective function (13) seeks to maximize the resulting total demand that is uncovered after interdiction. The first constraint (14) requires that r facilities are interdicted. A demand location is uncovered if $y_i = 1$, which can only be equal to 1 when all of the facilities that cover i (N_i) have been interdicted. This is enforced in the second set of constraints (15). The final two sets of constraints establishes integer restrictions on the variables. The r-interdiction median problem and the r-interdiction covering problem (the base models) can be solved by commercial integer programming software, Lagrangian relaxation, and heuristics.

One way to mitigate the worst-case vulnerabilities identified in these two base models is to allow a decision maker to first fortify some of the critical facilities, which makes these facilities immune to failure. This results in the r-interdiction median problem with fortification (Scaparra and Church [72]). The model has the same parameters and decision variables as the r-interdiction median problem with a new set of decision variables that capture fortification decisions:

$$z_j = \begin{cases} 1 & \text{if facility } j \text{ is fortified,} \\ 0 & \text{otherwise,} \end{cases} \qquad j \in F.$$

The r-interdiction median problem with fortification is formulated as a bilevel programming model. The upper-level problem captures fortification:

$$\min \quad H(z) \tag{18}$$
$$\text{subject to} \quad \sum_{j \in F} z_j = k, \tag{19}$$
$$z_j \in \{0,1\}, \quad j \in F, \tag{20}$$

whereas the lower-level problem captures interdiction of nonfortified facilities:

$$H(z) = \max \quad \left\{ \sum_{i \in I} \sum_{j \in F} a_i d_{ij} x_{ij} \right\} \tag{21}$$
$$\text{subject to} \quad \sum_{j \in F} s_j = r, \tag{22}$$
$$\sum_{j \in F} x_{ij} = 1, \quad i \in I, \tag{23}$$
$$\sum_{h \in T_{ij}} x_{ih} \le s_j, \quad j \in F, \tag{24}$$
$$s_j \le 1 - z_j, \quad j \in F, \tag{25}$$
$$x_{ij} \in \{0,1\}, \quad i \in I, j \in F, \tag{26}$$
$$s_j \in \{0,1\}, \quad j \in F. \tag{27}$$

The leader allocates k fortification resources in the upper-level problem in (19). The lower-level problem is similar to the r-interdiction median problem with the addition of one new set of constraints: $s_j \le 1 - z_j$, $j \in F$ in (25), which disallows a fortified facility from interdiction and links the upper- and lower-level problems.

Solving the bilevel programming model is challenging. Typical approaches for solving bilevel programming models include decomposition, duality, or reformulation, none of which are suitable for solving the r-interdiction median problem with fortification because of the structure of the lower-level problem. Scaparra and Church [72] introduce an implicit enumeration algorithm to solve the r-interdiction median problem with fortification. A stream of papers examines algorithms to solve these models (O'Hanley and Church [64]) as well as extensions to these models that allow for partial interdiction (Aksen and Aras [1], Aksen et al. [2]) and a trilevel interdiction model for preparedness and response (Irohara et al. [32]).

The interdiction model literature considers applications in transportation, power, and other networks. One novel interdiction model introduces a bilevel interdiction model for delaying a nuclear weapons project (Brown et al. [15]). The model considers an attacker who wishes to create a fission weapon as quickly as possible and an interdictor who seeks to delay the completion of the project for as long as possible by delaying certain activities needed to create a nuclear weapon. The attacker's model is a project management (critical shortest-path) problem where the completion of tasks involves using limited resources. Tasks can be expedited (shortened) by using additional resources. Certain milestones must be achieved via alternative courses of actions (i.e., different weapon materials and construction types), and there are various types of precedence constraints in sequencing tasks. The interdictor can delay the project by delaying certain tasks subject to an interdiction constraint. The decisions regarding which tasks to delay must be made before the project begins. Brown et al. [15] provide an algorithm that extends Benders decomposition and implement the algorithm using off-the-shelf project management software.

5. Disaster Preparedness

Preparedness addresses planning done prior to a disaster that is implemented when the disaster is imminent. Some of the research in this area focuses on prepositioning supplies and evacuation planning. Prepositioning supplies allows emergency responders to more quickly respond to a disaster, which in turns aids in recovery. Early models in the literature adapt siting models from the fire and emergency medical service literature to siting disaster resources. Two papers in this area include Belardo et al. [9], which focuses on siting oil spill response equipment near oil drilling areas, and Paul and Batta [68], which focuses on locating hospitals and allocating capacity to hospitals prone to natural disasters (e.g., those near a coastal region at risk for hurricanes). We note that many location models, particularly those that prelocate resources far in advance of a disaster event, are considered part of disaster mitigation.

Jia et al. [38] develop a model for locating emergency medical service (EMS) resources to prepare for a large-scale emergency. They consider the impact of large-scale emergencies by preparing for demand scenarios that may classify demand in different ways across demand areas, as well as different criteria for selecting eligible facility sites. Jia et al. [38] provide covering, p-median, and p-center model variations for locating facilities in preparation of a large-scale emergency. We will present the general location model. The model parameters include

- $J =$ the set facility locations;
- $I =$ the set of demand locations;
- $K =$ the set of possible emergency situations;
- $M_i =$ the population of location $i \in I$;
- $e_{ik} =$ the weight of location i under emergency scenario k, $i \in I$, $k \in K$;
- $\beta_{ik} =$ the likelihood that location i suffers large-scale emergency scenario k, $i \in I$, $k \in K$;
- $p_{jk} =$ the degree of disruption of facility j under emergency scenario k with $0 \le p_{jk} \le 1$, $j \in J$, $k \in K$;
- $d_{ij} =$ the distance from demand location i to j, $i \in I$, $j \in J$;
- $Q_i =$ the minimum number of facilities that must be assigned to location i for it to be considered covered, $i \in I$; and
- $P =$ the maximal number of facilities to locate.

The decision variables are as follows:

$$x_j = \begin{cases} 1 & \text{if a facility is located at site } j \in J, \\ 0 & \text{otherwise;} \end{cases}$$

$$z_{ij} = \begin{cases} 1 & \text{if location } i \text{ is assigned to a facility at } j,\ i \in I,\ j \in F, \\ 0 & \text{otherwise.} \end{cases}$$

As before, we present the median and coverage models. The p-median model for emergency scenario $k \in K$ is as follows:

$$Z_k = \min \quad \left\{ \sum_{i \in I} \sum_{j \in J} \beta_{ik} e_{ik} M_i d_{ij} z_{ij} \right\} \tag{28}$$

$$\text{subject to} \quad \sum_{j \in J} x_j = P, \tag{29}$$

$$\sum_{j \in J} z_{ij} p_{jk} = Q_i, \quad i \in I, \tag{30}$$

$$z_{ij} \le x_j, \quad i \in I,\ j \in J, \tag{31}$$

$$z_{ij} \in \{0, 1\}, \quad i \in I,\ j \in J, \tag{32}$$

$$x_j \in \{0, 1\}, \quad j \in J. \tag{33}$$

The objective function (28) minimizes the demand-weighted distance between the demand locations and the opened facilities. The first set of constraints (29) locates P facilities. The model implicitly assumes that all demands are served, which is achieved through the second set of constraints (30) that assign Q_i facilities to each demand location. The third set of constraints (31) ensures that demand locations are only assigned to open facilities. The final two sets of constraints enforce binary decision variable values.

Let $N_i = \{j \mid d_{ij} \le D_i\}$ be the set of facilities that cover (service) demand location $i \in I$, where D_i is the longest distance from demand point i a facility may be to cover i's demand. Let new decision variables (in addition to x_j, $j \in J$) include the following:

$$u_j = \begin{cases} 1 & \text{if location } j \text{ is covered, } i \in I, \\ 0 & \text{otherwise.} \end{cases}$$

Similarly, the covering model for emergency scenario $k \in K$ is as follows:

$$Z_k = \max \quad \left\{ \sum_{i \in I} \beta_{ik} e_{ik} M_i u_i \right\} \tag{34}$$

$$\text{subject to} \quad \sum_{j \in J} x_j \le P, \tag{35}$$

$$\sum_{j \in N_i} x_j p_{jk} \ge Q_i u_i, \quad i \in I, \tag{36}$$

$$u_i \in \{0, 1\}, \quad i \in I, \tag{37}$$

$$x_j \in \{0, 1\}, \quad j \in J. \tag{38}$$

The objective function (34) maximizes weighted coverage. The first set of constraints (35) locates P facilities. The second set of constraints (36) identifies which demand locations are covered. The final two sets of constraints enforce binary decision variable values.

The resulting models can be used to prelocate ambulances (facilities) at preselected stations. Jia et al. [38] illustrate the models with examples that include a dirty bomb attack, a terrorist attack using anthrax, and a terrorist attack using smallpox. The models provide insight into identifying tailored hospital locations for large-scale emergencies that take into account the unique attributes of these emergencies.

Evacuation is another major research area within preparedness. Evacuation is needed for many disasters, including hurricanes, tropical storms, wildfires, floods, and nuclear emergencies (see Papamichail and French [67]). After the decision to evacuate has been made (see Regnier [71]), detailed plans for evacuation guide the flow of traffic. Models and algorithms used in evacuating and routing include maximum flow network models, facility location models, the traveling salesman problem, and the vehicle routing problem. Sherali et al. [74] propose an evacuation model for hurricane and flood conditions using network flow models. The model proposes locating hurricane shelters (sink nodes in the network) and then prescribes an evacuation plan and seeks to minimize the total time spent by the evacuees (from source nodes) seeking shelters in the network system. The model is formulated as a nonlinear mixed-integer programming model. Heuristic and exact implicit enumeration algorithms are proposed for identifying optimal and near-optimal solutions. Cova and Johnson [21] propose a network flow model for identifying evacuation routes on a complex road network by focusing on lane-based routing. They formulate the model as an integer extension to the minimum cost flow problem. The model generates routing plans that reduce delays during evacuation that occur at traffic-crossing intersections.

6. Disaster Response

The discrete optimization literature for disaster response addresses a range of activities aimed at protecting and maintaining a system as well as at responding to emergencies in real time. This section outlines the literature on response, routing, and relief.

6.1. Emergency Response

Emergency response to routine emergencies that arise from 911 calls for fire, police, or EMS service has been an active area of research since the early 1970s. The most relevant papers in this area develop fire engine and ambulance dispatching models. These papers seek to assign vehicles to calls in real time as calls for service arrive to the system. One of the goals is to understand when to dispatch the closest vehicle to a patient and when to ration the closest vehicle (i.e., dispatch a more distant vehicle instead) in anticipation of a more emergent call. Another goal is to understand how many ambulances or fire engines to dispatch (Chelst and Barlach [18], Ignall et al. [31], Swersey [77]). Few papers in this area focus on large-scale emergencies. However, the ideas and methods translate to disasters since both focus on delivering time-sensitive service to customers. Additionally, both focus on public welfare, and therefore, issues such as equity emerge for both routine and large-scale emergencies.

Fire, police, and EMS services are public services. Different public service departments operate with different sets of rules pertaining to how to use resources and personnel. In many settings, vehicles return to a home station when not servicing calls (i.e., static vehicle locations), which is reflected in many papers in the literature. Jarvis [37] introduces a Markov decision process model for identifying dispatch policies for a single type of vehicle that minimizes the average distance traveled to a call. McLay and Mayorga [50] develop a Markov decision process for dispatching ambulances to prioritized patients to maximize expected coverage. They extend this model to consider "fair" dispatching policies (McLay and Mayorga [49]). Ansari et al. [5] develop a mixed-integer programming model to simultaneously locate and dispatch ambulances to calls by creating a series of districts surrounding each open station. Another stream of literature focuses on how to relocate vehicles such as ambulances after they finish service (dynamic locations) to better prepare for future calls using optimization (Berman [10, 11], Gendreau et al. [29]) or approximate dynamic programming (Maxwell et al. [44, 45], Schmid [73]).

However, all of these papers implicitly assume that the data for estimating the model inputs are accurate and that the system experiences low traffic (i.e., long queues do not form)—two issues that are not valid for disaster response. These underlying assumptions limit the application of the models to situations when responding to large-scale emergencies. Therefore, we next focus on response for relief efforts.

6.2. Routing and Relief

Routing for relief and delivering aid requires delivering time-sensitive commodities to customers. Özdamar et al. [66] propose a model for delivering commodities after a disaster. The proposed model integrates the multicommodity network flow problem and the vehicle routing problem (VRP) and seeks to deliver aid on a multimodal transportation network. Mete and Zabinsky [58] propose a stochastic optimization model for prelocating (preparedness) and distributing (response) medical supplies after a disaster, where the focus is on last-mile distribution of relief. The model enumerates all routes and assigns vehicles to routes in a capacitated assignment problem.

Campbell et al. [16] focus on routing supplies for relief efforts. They note that classic routing models such as the traveling salesman problem (TSP) and the VRP do not reflect the operations and priorities in the aftermath of a disaster. Campbell et al. [16] provide two routing models that are variants of the TSP and VRP. They consider (1) a minsum objective that minimizes the sum of arrival times and (2) a minmax objective that captures the beginning time of the last customer. The models are used to identify tours of customers labeled 1 to n. All tours start from a designated depot labeled 0. The parameters include the following:

- $N = \{1, \ldots, n\}$ = the set of customers (nodes),
- $N_0 = N \cup \{0\}$ = the total set of nodes including the depot (0),
- t_{ij} = travel time between the nodes i and j in N_0, and
- T = a sufficiently large number.

The decision variables include

$$x_{ij} = \begin{cases} 1 & \text{if the vehicle travels from } i \text{ to } j, \\ 0 & \text{otherwise;} \end{cases}$$

$$a_i = \text{the arrival time at customer } i.$$

They introduce an integer programming model with the minsum objective function value:

$$z = \min \sum_{i \in N} a_i \tag{39}$$

$$\text{subject to} \quad \sum_{j \in N_0} x_{ij} = 1, \quad i \in N, \tag{40}$$

$$\sum_{j \in N_0} x_{ij} - \sum_{j \in N_0} x_{ji} = 0, \quad i \in N_0, \tag{41}$$

$$t_{ij} + a_i \leq a_j + T(1 - x_{ij}), \quad i, j \in N, \tag{42}$$

$$a_i \geq t_{0i} x_{0i}, \quad i \in N, \tag{43}$$

$$x_{ij} \in \{0, 1\}, \quad i, j \in N_0. \tag{44}$$

The objective function (39) is the minsum objective that captures the sum of the arrival times. It can be contrasted with the VRP objective function that captures total distance traveled. The first set of constraints (40) ensures that each customer is visited by a vehicle. The second set of constraints (41) is the standard flow balancing constraints. The third and fourth sets of constraints ((42) and (43)) set the customer arrival times. The final set of constraints ensures that the travel variables are binary.

The model can be reformulated to capture the minmax objective by introducing auxiliary variable $\bar{a}$ to capture the last delivery time. The objective function (39) must be replaced by

$$\min \bar{a},$$

and the following constraints must be added:

$$a_i \le \bar{a}, \quad i \in N.$$

Campbell et al. [16] consider the relationships between the minsum and minmax objectives with the canonical TSP and VRP objectives to demonstrate the potential impact of the new objectives for disaster relief. They present heuristics for solving the minsum and minmax models based on insertion and local search techniques.

7. Disaster Recovery

Disaster recovery models focus on helping the system efficiently return to its pre-disaster capabilities. Most of the optimization models in this area focus on networks and model commodities such as transportation, water, power, and communications. One example is by Gutfraind et al. [30], who model recovery efforts as a network problem, where the goal is to schedule the network restoration (i.e., installation of nodes and arcs) that minimizes the total cost. Lee et al. [42] focus on the restoration of interdependent infrastructure systems and provide a discussion of pertinent issues to modeling interdependent systems.

Nurre et al. [63] study network design and scheduling decisions that can be used for a variety of infrastructure systems (e.g., power, communication, transportation). The problem involves scheduling the installation of a set of arcs in a network over time. Flow can be directed over the new components once the installed components become operational. The objective is to maximize the cumulative flow on the network over a fixed time horizon.

The model uses the following parameters:

- $G = (N, A) =$ a network with nodes N and arcs A;
- $A' =$ the set of arcs that can be installed on the network;
- $K =$ the number of parallel identical work groups that can install network components;
- $S \subset N =$ the set of supply nodes with supply s_i, $i \in S$;
- $D \subset N =$ the set of demand nodes with demand d_i, $i \in D$;
- $w_i =$ weight associated with a unit of flow that arrives at demand node $i \in D$;
- $u_{ij} =$ arc capacity for arc $(i,j) \in A \cup A'$;
- $p_{ij} =$ processing time to install arc $(i,j) \in A'$;
- $T =$ length of the time horizon; and
- $\mu_t =$ weight associated with the performance of the network at time $t = 1, 2, \ldots, T$.

The decision variables include

1. x_{ijt} = the amount of flow on arc $(i,j) \in A \cup A'$ at time $t = 1, \ldots, T$;
2. v_{it} = the amount of demand met at node $i \in D$ at time $t = 1, \ldots, T$;
3. $\beta_{ijt} = \begin{cases} 1 & \text{if arc } (i,j) \in A' \text{ is operational at time } t = 1, \ldots, T, \\ 0 & \text{otherwise;} \end{cases}$
4. $\alpha_{ijkt} = \begin{cases} 1 & \text{if work group } k \text{ completes arc } (i,j) \in A' \text{ in time period } t = 1, \ldots, T, \\ 0 & \text{otherwise.} \end{cases}$

The integer programming model is formulated as follows.

$$z = \max \quad \left\{ \sum_{t=1}^{T} \sum_{i \in D} \mu_t w_i v_{it} \right\} \tag{45}$$

$$\text{subject to} \quad \sum_{(i,j) \in A \cup A'} x_{ijt} - \sum_{(j,i) \in A \cup A'} x_{jit} \le s_i, \quad i \in S, t = 1, \ldots, T, \tag{46}$$

$$\sum_{(i,j)\in A\cup A'} x_{ijt} - \sum_{(j,i)\in A\cup A'} x_{jit} = 0, \quad i \in N\backslash\{S\cup D\}, t = 1,\ldots,T, \tag{47}$$

$$\sum_{(i,j)\in A\cup A'} x_{ijt} - \sum_{(j,i)\in A\cup A'} x_{jit} = -v_{it}, \quad i \in D, t = 1,\ldots,T, \tag{48}$$

$$0 \le v_{it} \le d_i, \quad i \in D, t = 1,\ldots,T, \tag{49}$$

$$0 \le x_{ijt} \le u_{ij}, \quad (i,j) \in A, t = 1,\ldots,T, \tag{50}$$

$$0 \le x_{ijt} \le u_{ij}\beta_{ijt}, \quad (i,j) \in A', t = 1,\ldots,T, \tag{51}$$

$$\sum_{(i,j)\in A'} \sum_{s=t}^{\min\{T,\, t+p_{ij}-1\}} \alpha_{kijs} \le 1, \quad k = 1,\ldots,K, t = 1,\ldots,T, \tag{52}$$

$$\beta_{ijt} - \sum_{s=1}^{t}\sum_{k=1}^{K} \alpha_{kijs} \le 0, \quad (i,j) \in A', t = 1,\ldots,T, \tag{53}$$

$$\sum_{t=1}^{p_{ij}-1} \beta_{ijt} = 0, \quad (i,j) \in A', \tag{54}$$

$$\sum_{k=1}^{K}\sum_{t=1}^{p_{ij}-1} \alpha_{kijt} = 0, \quad (i,j) \in A', \tag{55}$$

$$\alpha_{kijt}, \beta_{ijt} \in \{0,1\}, \quad (i,j) \in A', k = 1,\ldots,K, t = 1,\ldots,T. \tag{56}$$

The objective function (45) maximizes the total weighted flow over the time horizon. The first three sets of constraints (46)–(48) are typical network flow constraints in time period t. The next three sets of constraints (49)–(51) ensure that the flow and the flow delivered do not exceed the arc capacities and the demand. The next four sets of constraints (52)–(55) link the network design decisions with the scheduling decisions. The seventh set of constraints (52) ensures that work group k installs one arc at a time. The eighth set of constraints (53) ensures that an installed arc at time t was completed before time t. The 9th and 10th sets of constraints (54) and (55) ensure that an installed arc is not completed before its required processing time. The last set of constraints ensures the binary restriction on variables.

Nurre et al. [63] provide valid inequalities based on shortest processing time path inequalities, flow cover equalities, and β-conservation inequalities. They also provide a heuristic that selects the next set of arcs to install by exploiting the residual path optimality conditions. The analysis demonstrates that effective plans for repairing the network are not intuitive, which suggests that the model provides value for network recovery.

8. Conclusions and Recommendations

Managing disasters and improving homeland security involve using scarce resources and weigh multiple criteria. Operations research is ideally suited to manage disaster operations because it provides a suite of methodologies for managing scarce resources and making trade-offs between important criteria. Discrete optimization models are well suited for disaster management, preparedness, and response since many of the problems involve discrete decisions such as location, assignment, and network flows. This INFORMS *TutORials in Operations Research* has demonstrated the importance of discrete optimization models and algorithms by showing that they play a critical role throughout the disaster life cycle and across different types of disasters. Many of the new models presented in this INFORMS *TutORials in Operations Research* are focused on an individual problem; however, the models have a broader applicability. Models for hurricane evacuation, for example, can be applied to other evacuation problems resulting from flood, wildfires, and WMD attacks. Although there are many classes of discrete optimization models, models for homeland security and disaster problems generally cannot use canonical discrete optimization models (e.g., the vehicle routing problem) and instead explore new model variants.

There are numerous problems in disaster management and homeland security that can benefit from discrete optimization methodologies, such as providing response paradigms that coordinate resources across multiple agencies and recovery models that focus on interdependent systems. Additionally, there is a need to expand the scope of the models to consider the impact of big data (in both volume and velocity) that are collected before, during, and after a disaster event. This INFORMS *TutORials in Operations Research* focuses on *physical* disasters resulting from natural or man-made (e.g., terrorism) causes. Most of the models for physical disasters cannot be easily adapted to consider cyber threats or disasters, and therefore, there is a need to broaden the scope of disasters to accommodate emerging areas.

In summary, the issues discussed here represent but the tip of the iceberg. There are many additional challenges in homeland security and disaster management that could benefit from discrete optimization. Thus, discrete optimization methodologies can be used not only to gain insight into ways to improve disaster management and security operations and performance but also to make a lasting impression on our nation's security and resilience.

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