Quantitative modeling in disaster management: A literature review

A. E. Baxter
H. E. Wilborn Lagerman
P. Keskinocak

The number, magnitude, complexity, and impact of natural disasters have been steadily increasing in various parts of the world. When preparing for, responding to, and recovering from a disaster, multiple organizations make decisions and take actions considering the needs, available resources, and priorities of the affected communities, emergency supply chains, and infrastructures. Most of the prior research focuses on decision-making for independent systems (e.g., single critical infrastructure networks or distinct relief resources). An emerging research area extends the focus to interdependent systems (i.e., multiple dependent networks or resources). In this article, we survey the literature on modeling approaches for disaster management problems on independent systems, discuss some recent work on problems involving demand, resource, and/or network interdependencies, and offer future research directions to add to this growing research area.

1. Introduction

Disaster management activities typically take place in four phases: mitigation, preparedness, response, and recovery [1, 2]. Many governmental and non-governmental organizations and companies in the private sector [3] make disaster preparedness and response plans and participate, sometimes collaboratively, in the corresponding activities [4]. During the preparedness phase, logistical decisions (where to locate distribution centers, prepositioning of relief supplies, planning of evacuation routes, debris management plans, etc.) are made to increase the effectiveness of the response and recovery operations. During the response and recovery phases, the delivery of and access to goods (e.g., blankets, water, food, and medical supplies) and services (e.g., search and rescue, medical) depend on the overall condition of the infrastructure and the operational capabilities and capacities of the supply chains. Given the magnitude of post-disaster relief requirements and the complex relationships between supply chains, infrastructure network restoration and resource allocation/distribution decisions are non-trivial.

Large-scale disasters often require extensive restoration and response efforts; given the negative consequences of prolonged disruptions, efficient (prompt) and effective action is essential. For example, the effects of Hurricane María in the six months following the storm are now estimated to have caused a death toll of nearly 3,000 [5] due to prolonged effects of unrestored services (electricity, water distribution, etc.) to communities. However, the initial estimate from the Puerto Rican government was 63, which only reflected the deaths due to the immediate consequences of the hurricane. Optimization of disaster management decisions is critical not only for enabling immediate action, but also for avoiding long-term negative consequences due to lack of access to essential goods and services.

This article provides a review of the current literature on mathematical modeling of independent systems associated with disaster preparedness, resource allocation during the response phase, and infrastructure restoration efforts in both the response and recovery phases. We also include some relevant literature on non-disaster emergency services management. Additionally, we present some of the emerging literature focused on improving disaster management efforts given system-level interdependencies among and between infrastructure networks and relief resources. For example, resources such as ambulances and water rescue services may need to coordinate to meet demand in the wake of a hurricane. From an infrastructure perspective, individuals in need of medical services may be unable to contact healthcare facilities if cellular networks

Digital Object Identifier: 10.1147/JRD.2019.2960356

are down; repair of power lines may be delayed due to damage or debris on the roads. Decisions associated with resource allocation and network restoration may impact each other; for instance, the efficient distribution of relief resources is dependent on the repair of transportation networks. Potential cascading effects add to the difficulty of these decisions. Incorporating interdependencies adds another layer of complexity to the decisions. Therefore, we first provide a survey of independent systems and then discuss potential interdependencies.

This article focuses on the methodological aspects of disaster management, acknowledging that the development of accurate and useful models is often motivated by human agency and empirical results. For reviews of the growing literature on empirical research as well as strategic interactions between decision-makers in disaster management, we refer the reader to [6–8] and [9, 10], respectively.

The remainder of this article is structured as follows. In Section 2, we discuss the preparedness phase of disaster management, focusing on prepositioning and facility location problems. Section 3 provides a review of resource allocation literature during disaster and emergency response, addressing relief routing/delivery and scheduling. In Section 4, we examine network restoration in the response and recovery phases, including incremental network design and network improvement and vehicle routing and scheduling. In each section, we survey the literature on independent systems, limiting our review to recent work (within the past 20 years), with the majority of the papers published within the last decade. We then define the types of interdependencies that may exist in each setting, provide examples, and discuss future research directions.

2. Prepositioning and facility location

Many logistical decisions are made during the preparedness phase of disaster management, such as response planning (including training and exercises), assessments of infrastructure and supply chain functionality, evacuation planning [11], locations of distribution centers and supply prepositioning, infrastructure network vulnerability analysis [12–14] and design, etc. Various papers [15–26] address the problem of prepositioning supplies for disaster management, which is an example of supply chain network design. Making facility location and supply prepositioning decisions prior to a disaster is necessary to mitigate post-event supply chain disruptions. Effective prepositioning of relief supplies can reduce the overall supply chain costs and post-disaster response time [27]. The goal is to minimize travel time from supply locations to demand locations and/or achieve maximum satisfaction of realized demand (post-disaster).

A common approach to formulate the prepositioning problem is a two-stage scenario-based programming model [15–24] in which the first stage focuses on decisions prior to the disaster (i.e., under some uncertainty) and the second stage considers decisions after the realization of a specific post-disaster demand scenario. First-stage decisions include supply prepositioning locations and inventory levels at each location, initial investment, operating costs, average response time with or without prepositioning, etc. Under the realization of a demand scenario, second-stage decisions determine the quantities of supply to send to demand locations from supply locations, transshipment of supplies between supply locations, delivery times, etc. The objectives include minimizing the expected average response time [15, 16], maximizing the total expected demand coverage [17], minimizing the expected number of casualties [18], minimizing costs [19–21] (including the cost of facilities, inventories, delivering supplies, and penalties for unmet demand), or achieving a particular service level or overall social impact [22] while keeping logistical costs low. Both [23] and [24] consider multiobjective models. Bozorgi-Amiri et al. [23] use compromise programming to solve their model with the objectives of minimizing expected costs and maximizing the satisfaction of affected areas by minimizing the sum of the maximum supply shortage. Mohammadi et al. [24] propose a multiobjective particle swarm optimization algorithm to solve their model with the objectives of minimizing costs, maximizing total expected demand covered, and minimizing the maximum difference in the satisfaction rate between the demand locations in each scenario. In contrast to the aforementioned papers, Manopiniwes et al. [25] develop a deterministic model with a single demand scenario (i.e., demand is known in advance) with the objective of minimizing total operational costs.

Many interdependencies can arise in the facility location and supply prepositioning problem. For instance, supply points may need to collaborate to reposition relief supplies in the event of facility damages across the network. Additionally, if multiple commodities are being prepositioned, then certain commodities may depend on the presence of other commodities. For example, facilities that store food might also have to store water. While including these interdependencies in models adds complexity, doing so can create a more accurate representation of the disaster scenario. Within the supply prepositioning and facility location literature, Davis et al. [26] consider coordination among supply points. They categorize their supply locations (warehouses or distribution centers) as affected and non-affected. Affected warehouses fall within the geographical range of a disaster (i.e., are subject to facility damage) and non-affected warehouses fall outside the potential disaster area. There is no coordination between warehouses if there is no reserve capacity or inventory for relief operations at warehouses that have been deemed non-affected. Limited coordination occurs when there is no inventory available at non-affected warehouses to support relief operations, but there is capacity to accept incoming supply from affected warehouses prior to the disaster event.

Potential future work can continue to expand on the aforementioned interdependent situations. There is limited literature on incorporating potential dependencies among supply locations in the relief chain. For example, locations of shelter facilities may be fixed prior to a hurricane. However, current technology cannot always predict the path of a hurricane, and the disaster realization may leave facilities damaged. These facilities would then rely on collaboration with undamaged facilities in the surrounding area to meet relief demand. During Hurricane Katrina, more than 30,000 people had taken shelter at the Mercedes-Benz Superdome in New Orleans, LA, USA. As the Superdome became damaged and resources were depleted, about 25,000 Katrina victims were bussed to Houston, TX, to take shelter in Houston's Astrodome [28]. Furthermore, determining the locations of facilities may depend on the resiliency of other infrastructure networks (i.e., transportation network, power network, etc.). For example, when determining the location of supply facilities, planners may need to consider the likelihood of potential damage to the surrounding transportation network that could prevent delivery of supplies to demand locations. Future research could address such network interdependencies when making facility location and supply prepositioning decisions.

3. Resource allocation during disaster and emergency response

In the immediate aftermath of a disaster, relief supply chains are activated (since commercial supply chains are typically inadequate to meet demand); delivering goods and services to the affected communities [2] and restoring the infrastructure become major focus areas. In this section, we discuss resource allocation decisions during disaster response, primarily focusing on the delivery of goods and services to affected populations, given the current state of the infrastructure and available resources. The uncertainty and changing nature (type, location, magnitude, etc.) of demand and supply and the potential interdependencies between decisions and their system-wide impacts contribute to the complexity of resource allocation decisions.

3.1. Relief routing/delivery

During disaster response, vehicles carrying relief supplies must be routed (assigned a sequence of tasks/demands in different locations in a network) and dispatched (if tasks arrive dynamically, e.g., first-come–first-served) to minimize the cost/time of delivery while ensuring that relief demand is satisfied. In this section, we discuss delivery of disaster relief supplies/services and deployment of emergency medical services.

3.1.1. Distribution of relief supplies

Distribution of relief supplies is one of the major problems studied in the disaster response phase and is addressed within the vehicle routing literature. In particular, the roads and locations (of demand, supply, and other transition points) are often modeled as a network with edges and nodes, respectively, and vehicles are routed across this network to meet demand for relief items in the affected areas. These decisions may be affected by some types of uncertainty (e.g., the type and quantity of demand and supply across different locations in the network, damage on the roads/edges limiting passage or access to certain areas). Furthermore, given the urgency of disaster response, routing decisions can be subject to unique constraints (e.g., delivery time restrictions, penalties for unmet demand). De la Torre et al. [29] provide a recent survey of relief routing models.

Various papers [30–32] present mixed integer programming models to determine vehicle routing and resource allocation decisions during humanitarian relief operations. De Angelis et al. [30] study efficient emergency food delivery by air for the World Food Programme (WFP) with the objective of maximizing total satisfied demand. In contrast, [31, 32] consider multiple objectives. Viswanath and Peeta [31] identify critical supply delivery routes for earthquake response, seeking to minimize total travel time over the selected routes and maximize demand coverage. Huang et al. [32] consider three metrics: efficiency (i.e., total travel time), efficacy (i.e., response time and sufficiency of deliveries), and equity (i.e., deviation in demand satisfaction across the network). These metrics are important for humanitarian relief distribution as aid organizations need to consider both the potential logistical costs and the expected demand coverage in affected areas, under limited resources or budget.

Given the unpredictable nature of disaster scenarios, recent papers have included aspects of uncertainty in their models (e.g., uncertainty of demand in affected areas, uncertainty of supply damage/availability, etc.). A common approach is to use two-stage stochastic optimization models [33–37], where the first stage represents the initial decisions (typically made prior to the disaster) and the second stage includes (corrective) decisions made post-disaster after the realization of a particular scenario. The models in [33–35] combine the facility location and supply prepositioning problem with the relief routing and delivery problem. The first stage decides distribution center locations and inventory decisions. After demand has been realized, the second stage determines delivery amounts and vehicle routes. The objectives in these models include minimizing the total costs and transportation time, where [33, 34] include a penalty for unfulfilled demand. The first-stage decisions in [36, 37] involve efficient route planning (i.e., which routes to consider for relief delivery in the given network); however, their second-stage decisions differ. Tricoire et al. [36]

determine the supply amounts to deliver across the routes. Shen et al. [37] develop a recourse strategy that allows for multiple route adjustments in the second (operational) stage, where they may adjust the resource quantity sent by each vehicle, modify the selected routes, or re-plan the optimal routing after demand realization.

When deciding how to efficiently route and dispatch resources during disaster response, there may be several interdependencies in the system. For example, if multiple, nonhomogeneous resources need to be delivered, this could require coordination between the vehicle fleet to route all resources across the network and meet respective demands (i.e., resource interdependencies). Furthermore, different routing systems (i.e., relief routing, evacuation routing, rescue operations, etc.) may require collaboration in order to efficiently use the shared network (i.e., these operations are dependent on the underlying transportation network).

Some of these interdependencies have been addressed in the literature [38–41]. Balcik et al. [38] classify relief resources based on their demand characteristics (Type 1 and Type 2). Type 1 items are required once at the beginning of the planning horizon (e.g., tents, blankets, mosquito nets, etc.) and accumulate penalty costs over time for each unit of unsatisfied demand. Type 2 items are required regularly throughout the planning horizon (e.g., food, hygiene kits, etc.) and cannot be backordered (i.e., unmet demand is lost). Each vehicle can accommodate both types of items (nonhomogeneous loads). Their modeling approach has two phases: Phase 1 generates all feasible delivery routes for each vehicle. Phase 2 determines which delivery routes to use (from the set generated in Phase 1), delivery amounts of each type of item, and vehicle loads for the coming periods with the objective of minimizing routing costs and penalty costs for backordered Type 1 demand and lost Type 2 demand. Coordination of logistics support and evacuation operations in disaster response is considered in [39] and [40]. Both papers develop a multicommodity network flow model to minimize the weighted sum of unsatisfied demand over all commodities and the weighted sum of unserved wounded people. Finally, Zhang et al. [41] study the allocation of emergency resources considering the possibility of secondary disasters (e.g., extreme flooding causing a mudslide).

Interdependencies in the distribution of relief supplies during the humanitarian response phase are an important area of research that has not been well studied. The case of nonhomogeneous relief routing with multiple decision-makers could be examined; for example, emergency response may depend on the prompt delivery of medical supplies as well as personnel to the affected regions so that medical treatment can be provided to those in need. Additionally, the dependency of relief routing on the state of the underlying transportation network can be addressed. After Hurricane Dorian, the governor of Puerto Rico stated that a major issue was finding transportation to distribute relief aid. The mayor of one affected mountain municipality said that because of debris-covered roads, their community was "waiting for food and water, even though nine pallets sent by the federal government sat at a regional distribution center an hour away" [42].

3.1.2. Ambulance dispatching

Ambulance dispatching is an example of a relief service distribution. Ambulances are assigned to requests according to some dispatching rule (e.g., first-come–first-served) in order to minimize the travel/wait time of a service request and/or maximize the number of requests serviced with a certain time horizon. Efficient delivery of ambulance services is critical; ideally, ambulance response time should be short (e.g., within 9 minutes of a request). For a thorough review of the ambulance dispatching literature, we refer the reader to recent reviews [43, 44].

In the static (offline), deterministic version of the ambulance dispatching problem, all requests for emergency medical services are known ahead of time. Gong and Batta [45] and Van den Berg and Van Essen [46] develop deterministic models to allocate ambulances for a post-disaster relief operation, considering a single type and two types of ambulances (advanced and basic life support), respectively.

To capture the dynamic arrival of demand and decisions over time, ambulance dispatching problems are often modeled as queues with the objective of maximizing the expected coverage (number of requests served) in a specified amount of time, under the following common assumptions.

1) Requests for service arrive at independent rates following a Poisson process.
2) One server/unit is dispatched in response to each incoming request.
3) The request is added to a queue (wait for a server to become available) if there are no free units.
4) The queue operates on a first-come-first-served (FCFS) basis.

Various papers relax and/or extend some of these assumptions. Yoon and Albert [47] consider one type of ambulance, whereas [48, 49] consider two types. In both [47] and [48], the FCFS assumption is relaxed; instead, incoming calls are prioritized based on severity (i.e., urgency of medical assistance).

Various papers [50, 51, 54] model the single-type ambulance dispatching problem as a Markov decision process. Maxwell et al. [50] consider non-Markovian elements in the system, such as service times that follow a general (not necessarily exponential) distribution and deterministic travel times. Both [50] and [54] prioritize calls based on severity.

McLay [49] considers advanced life support (ALS) and basic life support (BLS) ambulances and classifies requests (Priority 1, 2, and 3). Priority 1 and 2 requests are or could be life-threatening, respectively, while Priority 3 requests are not life-threatening. When both ALS and BLS units are available, deployment protocol is to send ALS units to Priority 1 requests, either type to Priority 2 requests (with ALS preferred), and BLS units to Priority 3 requests. In addition, if no ALS units are available, BLS units may be dispatched to Priority 1 requests in order to stabilize the patient until an ALS unit becomes available. If a BLS unit is dispatched first to a Priority 1 request, an ALS unit must also be dispatched when available. The objective is to maximize the expected number of Priority 1 requests serviced, given the interdependencies between the two types of ambulances.

Future research could consider the dependencies among different types of emergency response vehicles (ambulances, fire engines, police, etc.) and how these dependencies affect resource allocation and coordination decisions. Furthermore, these different vehicle fleets may belong to and be operated by different agencies. Potential research includes addressing how these different agencies could collaborate to meet the requests, considering the fact that some requests might need multiple resources simultaneously or successively. For example, after a major multicar traffic accident, multiple ambulances may need to respond while coordinating with police and/or fire trucks.

3.2. Scheduling

In the aftermath of a disaster, resources are limited and the prioritization/scheduling of resources and services (e.g., search and rescue, relief supplies, medical personnel) across different geographic areas and populations has impact on response efforts both short- and long-term. The value of post-disaster relief allocation decisions often changes with time. Given widespread high demand, it is important to consider the different impacts and consequences of delays in the deliveries of goods or services to different demand locations. Relief distribution scheduling decisions include the assignment and delivery times of relief supplies to demand locations to minimize time-based objectives subject to resource availability constraints.

Various papers [52, 53, 55–58] model efficient scheduling of emergency resources that are categorized by their capabilities. Each demand incident has specified requirements (e.g., fire brigade, search-and-rescue teams, police) and can be served by those resources that have the required capabilities. The allocation of resource units (agents) to disaster incidents with the objective of minimizing the total weighted completion times over all incidents has been studied in [52, 53, 55, 56], utilizing mixed integer quadratic programs [52, 53] and mixed integer linear programs [55–58]. Altay [57] developed a multiobjective model, minimizing the weighted sum of total deployment (travel) time and total capability deficit (i.e., unfulfilled demand). Su et al. [58] focused on minimizing the weighted sum of travel times and total cost.

Many instances of relief scheduling during disaster response involve coordination and collaboration between different resources and disaster agencies. If resources have different capabilities or characteristics, then multiple units may need to collaborate to meet demand either by being scheduled sequentially or simultaneously. The relief scheduling literature [52, 55, 56, 58–61] addresses these interdependencies between resources.

During disaster response, after a certain demand has been satisfied, non-renewable resources (e.g., medical and relief supplies, food, etc.) are depleted, whereas renewable resources (e.g., emergency personnel, ambulances, rescue teams, etc.) can be made available again to meet additional demand. The models presented in [59–61] consider the efficient scheduling of both renewable and non-renewable resources. Bodaghi et al. [59] introduce a biobjective optimization model to minimize the total weighted time of meeting demand as well as the overall makespan of the relief operation (i.e., the distribution of emergency resources to the affected areas). Scheduling in [59] relies on coordinating the delivery sequence of renewable resources while dispatching non-renewable resources from distribution centers. The models developed in [60] and [61] consider coordinating the assignment and scheduling of non-renewable (medical and emergency supplies) and renewable (disaster medical assistance teams) resources with the objective of minimizing the total tardiness penalty across demand nodes. Lei et al. [61] use a rolling-horizon-based greedy heuristic to determine how to allocate medical supplies from distribution centers to patients.

Some papers address the multiresource scheduling problem in which there is some coordination or collaboration among resources with different capabilities [52, 55, 56, 58]. Collaboration is needed when not all of the requirements of a certain demand can be met by a single resource, i.e., multiple resources may be needed (simultaneously or sequentially) to meet a demand. Collaboration can be tight [58] or loose [52, 55, 56]. Loose collaboration allows for resource units to work independently to meet demand. Tight collaboration requires that all resource units needed by a particular demand be simultaneously available to meet that demand.

Current disaster relief scheduling research where there is collaboration between resources with different capabilities mainly focuses on loose collaboration, i.e., relief resources can arrive in any order to meet demand. Future research could develop strategies to address cases in which resources may need to arrive at demand incidents sequentially. For example, a demand incident may require a search-and-rescue team prior to the arrival of emergency medical services. There are also instances where tight collaboration might be necessary. During Hurricane Harvey, Montgomery County, TX, experienced severe flooding that cut off many patients' access to emergency medical services [62]; water rescue teams and emergency medical services had to coordinate to enable medical personnel to reach patients who were trapped in their homes. Further research into efficient tight collaboration strategies would be beneficial to accurately model and effectively address scenarios such as this. It would also be valuable to extend current resource scheduling models to address potential uncertainty in supply and consider demand incidents that arrive dynamically throughout the time horizon.

4. Network restoration

Restoring disrupted services to some level of normalcy (and enabling effective relief efforts) often hinges on repairing infrastructure networks. Transportation, electricity, communication, water, and other networks are essential to daily operations and survival. The more prolonged disrupted conditions become, the more danger is posed to community members due to limited access to basic services and supplies. A recent survey of disaster response literature (including network restoration) is provided by Çelik [63].

According to Rinaldi et al. [64], two networks are interdependent if "the state of each infrastructure influences or is correlated to the state of the other." The authors define types of interdependencies that exist between infrastructure networks: physical, cyber, geographic, and logical. *Physical interdependence* occurs when two networks' states depend on "material outputs" from each other. *Cyber interdependence* occurs when an infrastructure relies on the transmission of information. *Geographic interdependence* occurs when infrastructure networks in close proximity are affected by the same environmental event. Finally, *logical interdependence* occurs when the states of two networks depend on each other in ways other than the aforementioned relationships. In the following sections, we review existing infrastructure restoration literature and discuss the ways in which interdependencies are or could be considered, motivated by real-world examples.

4.1. Incremental network design and network improvement

Network design for infrastructure planning, facility location, or supply prepositioning (see Section 2) affect post-disaster response and recovery/restoration efforts. Network design literature is vast [65–70]. Decisions in network design often focus on resilience ("which includes the ability to withstand and recover rapidly from. . .natural disasters" [69] or "adapt to changing conditions, and reduce the magnitude and/or duration of disruptive events" [70]) considering the potential occurrence of disruptive events (natural or man-made disasters, deliberate attacks, large-scale system malfunctions or accidents, etc.). Disaster preparedness activities such as supply prepositioning and facility location are examples of emergency supply chain network design.

The aforementioned planning and preparedness activities directly impact recovery and response efforts. In this section, we provide examples from the incremental network design and network improvement literature focused on post-disaster infrastructure restoration. Rather than considering the design of a network from scratch, in incremental design or network improvement, there is a pre-existing network and decisions focused on restoring and/or improving that network. The goal is to achieve a particular intermediate performance level in the partially functional system, or a particular final design given some restrictions imposed by the pre-existing network.

4.1.1. Incremental network design

In the aftermath of a disaster, response and recovery efforts might focus on restoring the network (incrementally) to its previous state as quickly as possible while simultaneously minimizing the negative impact on the affected populations. In some cases, restoration efforts can include redesigning or rebuilding certain parts of the network to better meet current and future needs. A common feature of this literature is the focus on network performance throughout the planning period; at each stage of the restoration process, an objective is evaluated such as maximizing flow of relief supplies to demand points (i.e., to ensure that as much relief as possible is delivered while the network is partially functioning). The decisions include which edges of the network to restore or install at various points in time.

Incremental network design problems (IND) [71–73] provide insights into the process of making sequential decisions about the configuration of a network. The decision-maker sequentially selects single edges to add (or restore). The goal is to prioritize the edges to achieve the best cumulative objective (e.g., maximum flow, shortest path, minimum spanning tree) over the planning horizon. Note that "in some situations, the benefits of building a link will only materialize when other links have been built as well" [72]. This challenge is particularly prevalent in interdependent network restoration; the benefits of restoring particular edges often vary with time and each decision can have cascading effects throughout the network(s). Earlier literature provides a strong foundation for network design approaches to restoration problems on single networks; there are opportunities for development of similar fundamental results for interdependent network problems (general problem class complexity results, approximation algorithms, etc.).

4.1.2. Network improvement

Network improvement (or arc upgrading) starts with a pre-existing network design (a realistic characteristic of post-disaster restoration efforts) and restores and/or upgrades certain edges over time. In the context of disaster response, given a disrupted network (e.g., a road network), the decisions are which arcs to restore, enhance, or construct (and when) under various limitations (budget, time, resource availability, fixed relief facility locations, etc.). The goal is to establish a certain structure in the partially restored network subject to the constraints imposed by the design of the original network and factors such as the capabilities and speeds of the restoration crews.

Objectives of network improvement problems for infrastructure restoration vary across the literature, but the goal is often to ensure accessibility (i.e., enabling all individuals to obtain aid and supplies) across the network by establishing routes that allow travel to hubs such as cities, airports, relief distribution sites, and shelters. For example, in certain developing countries, rural communities rely on unpaved pathways for travel. During periods of heavy rain, these paths may become dangerous or impassable. While [74–76] seek to increase general accessibility of rural communities to essential services, their modeling choices differ. Murawski and Church [74] aim to maximize the number of residents who have access to healthcare facilities (located according to a predetermined network design) by improving roads under a limited budget. In contrast to the exact solution obtained by these authors, heuristic approaches are explored in the other two papers and are shown to provide high-quality solutions. Scaparra and Church [75] seek to maximize route efficiency in addition to all-weather road connectivity; the authors create a greedy randomized adaptive search procedure and path relinking heuristic to obtain approximate solutions. Maya Duque et al. [76] also consider rural road improvement via the accessibility arc upgrading problem (AAUP) in lesser developed communities. The authors provide two solution approaches: One exploits properties of the knapsack problem in cases where the AAUP network is a star or tree structure, and the other uses a neighborhood search method. Heuristic solution approaches such as these are valuable tools in practice where decisions need to be made in a timely manner.

Equity-constrained network design problems (i.e., fairness in benefits gained by network users due to improvements/upgrades) are addressed in [77] and [78]. Meng and Yang [77] consider the continuous network design problem (CNDP) under deterministic user equilibrium (DUE), choosing the arcs in a network on which to increase capacity. The authors use a bilevel optimization model that includes an equity constraint; by changing parameters of the problem, the authors can guarantee a certain level of equity in reduced travel costs associated with capacity changes. Chen and Yang [78] also study optimal arc capacity changes in CNDP subject to equity requirements and DUE in addition to a stochastic network design model. The longer term planning methods in [77] and [78] could be useful once the initial connectedness conditions in infrastructure networks are satisfied and decision-making shifts to extended-period restoration. Krumke et al. [79] provide several results regarding the quality and speed of approximation algorithms for node- and edge-based upgrading problems under various other restrictions and three objectives.

Interdependencies may affect which arcs are feasible to restore or upgrade at different points in an IND or network improvement model. For example, certain areas of the network need to be physically accessible before they can be restored (i.e., a disrupted arc in a graph cannot be restored if there is no feasible path to that arc from the nodes where the restoration resources are located). Restoration of a particular arc may be delayed due to other types of interdependencies as well; for example, it may be impossible to re-establish communication between two networks if the power supply to one or both of them has failed. Gay et al. [80] discuss how damage to radiation clinics, lack of communication between radiation oncologists, and lack of telephone and Internet services after Hurricane María resulted in a multitude of complications for radiation patients, who require precise treatment on a regular schedule. Some patients had to visit clinics and physicians that unfamiliar to them. The inability to communicate between facilities and access medical records posed complications for continuing treatment. These challenges highlighted the need for rapid restoration of reliable forms of communication post-disaster.

Changing environmental conditions, material and information flow, and resource availability in a community add complexity to restoration decisions by affecting multiple infrastructure networks and their interactions. In reality, design and improvement decisions for one infrastructure network are influenced by the state of other networks. At each decision point, the state of the system of infrastructure networks as a whole should be considered. Cascading benefits and penalties such as these have the potential to significantly impact decision-making. Disruptive events provide an opportunity to potentially improve the underlying network design by improving or upgrading existing network components or constructing new ones. Future work in network improvement and incremental network design could incorporate measures of vulnerability or resilience in models in an effort to improve the ability of infrastructures to withstand damaging events in the future. Additionally, future research could examine the tradeoffs between investments in upgrades on different infrastructure networks with the goal of guaranteeing some level of accessibility [74].

4.2. Scheduling and vehicle routing

In infrastructure restoration, there is often a time-dependent reward (penalty) for restoring (failing to restore) connectivity to a particular node or section of a network;

objectives in these scenarios include maximizing total reward, minimizing total penalty, minimizing the maximum time necessary to restore a particular part of the network, etc. The ability to simultaneously consider assigning and routing of restoration crews to tasks and the timeline for completing those tasks is important for interdependent network restoration. Scheduling approaches determine which restoration tasks to complete and when to complete them (and thus, what penalty or reward is accrued) using which restoration resources. Typically, each crew leaves from (and may return to) a particular location (depot) in the network.

In most post-disaster response settings, it is important to establish paths (connectivity) between the nodes in an infrastructure network to ensure accessibility. Kasaei and Salman [81] study two problems: one that is appropriate for ensuring fairness in decision-making (arc routing for connectivity, or ARCP) and one that allows prioritization of certain network components via the assignment of prize values (prize-collecting ARCP, or PC-ARCP). Depending on the objectives of decision-makers in post-disaster restoration scenarios, one of these models may be applicable. Maya Duque et al. [82] study restoration on a sparse network; their model creates paths from a depot to each node in the network and ensures that path lengths do not exceed a threshold (i.e., the nodes in the network are within a specified distance from the depot). By using a sparse network representation, the authors capture the challenges of connecting isolated demand locations (such as shelters, relief aid distribution points, and rural communities) to a central supply location such as a city or airport (i.e., the depot). Both [81] and [82] consider a single infrastructure network, a single depot (which can be interpreted as supply storage or another important hub of activity), and a single work crew that performs all restoration tasks.

In practice, it may be useful to incorporate a time limit on the restoration activities for an infrastructure network; decision-makers may determine that a certain level of connectivity must be achieved before, for example, a predicted secondary disaster or some point in time after which conditions for community members are considered increasingly dangerous. Akbari and Salman [83] present a model that assigns prize values to restoration tasks on a road network (similar to Kasaei and Salman [81]). The objective is to maximize the total collected prize value while requiring that restoration crews' routes are completed within a time limit. Similarly, Tuzun Aksu and Ozdamar [84] assign priorities to a predetermined set of road paths (which, upon restoration, will allow access to all locations in the network) and decide the order in which to repair arcs on the paths. The objective function incentivizes restoring high-traffic arcs early. The goal of this work is to ensure that evacuation efforts are able to proceed in a timely fashion, thus reducing extended risks to community members. This model also optimizes restoration resource allocation to districts in the community so that each area is addressed equitably. Kim et al. [85] explore the unpredictable nature of post-disaster operations immediately after the event. The authors determine a restoration schedule that minimizes total damages as well as the completion time of the restoration. This work's purpose is to capture the potentially rapidly changing conditions under which restoration crews must work; after a certain amount of time, the damage to the isolated components of the network drastically increases; hence, the model incentivizes early establishment of access to all areas in the network. Çelik et al. [86] study the stochastic debris clearance problem; a road network is partially blocked by post-disaster debris (thus hindering relief distribution), where the debris amounts (and corresponding clearance capacity and times) are uncertain. Debris clearance must occur in the first days following a disaster to allow further restoration and recovery activities. In each time period, debris clearance and relief distribution decisions are made to maximize the benefit gained from satisfying demand; new information about the debris amounts in recently connected parts of the network becomes available (which impacts future clearance and flow decisions) in each time period. The authors model this problem as a partially observable Markov decision process and propose heuristic solution approaches. The above papers consider multiple [83, 84] and single [85, 86] restoration crews, respectively. The papers reviewed in the remainder of this section all consider multiple crews.

The availability of multiple crews (resources) enables simultaneous restoration activities (i.e., addressing multiple components in the network concurrently). Network restoration literature with multiple resources considers resource/crew interdependencies and coordination, assignment of network components to crews, and efficient travel of crews on the network (routing). The scheduling of each crew depends on which arcs are accessible at a given time and, thus, depends on the previous actions of all other crews.

There is limited literature on collaboration between restoration resources. Averbakh [87] minimizes the makespan (the recovery time of the last node) of restoration in a transportation network. Their model allows restoration crews to work together to complete tasks; when this occurs, the new restoration speed is the sum of the speeds of the crews. Morshedlou et al. [88] also model dynamic restoration rates (i.e., the effects of collaboration between crews) and, in addition, incorporate travel times of restoration crews while scheduling and routing repair vehicles on an unaffected road network to repair damaged components of another network (e.g., a power network). Using a measure for infrastructure resilience (a function of network performance), they compare partial and full restoration at the network component level. In partial restoration, disrupted components can contribute to the overall performance of the network before their restoration is complete (i.e., they may be usable, but at a decreased capacity).

Ulusan and Ergun [89] decide resource flow and the schedule of work crews on a disrupted road network such that the cumulative benefit (which decreases exponentially over time) for satisfying demand is maximized over the planning horizon. The goal is to achieve adequate operation of the emergency service network (distribution of relief supplies and transportation of casualties) such that all disaster sites can be served as quickly as possible. They introduce a new measure for the criticality of disrupted transportation network edges that is used in a heuristic solution approach to prioritize the restoration of network components. Similarly, Iloglu and Albert [90] study the interdependency between road network recovery and emergency response services. Restoration/addition of arcs (repair of roads) in the network are scheduled over the time horizon; emergency responders are able to travel on arcs (roads) once they are completed. The objective is to minimize the cumulative weighted distance (over time) between demand points and emergency responders.

Integrated network design and scheduling (INDS) problems were proposed by Nurre et al. [91] and are closely related to incremental network design [71–73]; network performance is measured at intermediate steps (after implementing design decisions) in the restoration process (as opposed to only on the completed network), and the objective is to optimize cumulative performance over the planning period. Because performance is evaluated repeatedly, scheduling decisions greatly impact the overall objective. Parallel identical machines (i.e., restoration crews with identical work speeds) INDS problems are examined by Nurre and Sharkey [92]. The authors explore a variety of metrics (maximum flow, minimum-cost flow, three versions of shortest path, and minimum spanning tree), each with two objective function variations (cumulative network performance over time and minimum time to achieve a threshold level of performance) for a total of 12 problems. The parallel identical machine INDS problem is shown to be NP-hard for all explored versions. Given the complexity of the problems, the authors introduce dispatching rules for work crews that result in near-optimal solutions for the objectives considered.

The papers provided in this section thus far consider restoration of a single infrastructure network; in practice, however, infrastructures often rely on each other in some way(s) to function. All of the remaining work in this section models multiple interdependent infrastructure networks.

Both [93] and [94] use minimum-cost network flow models to determine a restoration schedule for a system of interdependent infrastructure networks. The models include one type of interdependency: physical or "input" interdependencies in which the performance of one infrastructure network relies on service or output from another network. González et al. [93] indicate the constraint modifications that would be necessary to incorporate logical and cyber interdependencies in their model. They present a static, deterministic, single-time-period optimization model but include a discussion about the potential to solve their model repeatedly; doing so would allow for updating parameters such as costs, budgets, and resource availability to reflect management decisions throughout the restoration process. In contrast, Cavdaroglu et al. [94] present a time-indexed optimization model (i.e., decide which restoration tasks to perform in every time period).

Network restoration scheduling under physical interdependencies with an aim to increase resilience in disaster-affected communities is considered in [95] and [96]. Both papers maximize resilience while minimizing restoration costs subject to resource and interdependency constraints. Almoghathawi et al. [95] define a resilience measure that is time-dependent and compares network recovery with performance loss incurred by the disruptive event. Barker et al. [96] introduce a social vulnerability index that is calculated for each disrupted node in each infrastructure network; higher restoration priority is placed on nodes that are more vulnerable.

Some existing research [90] considers emergency response when scheduling restoration activities; future work in this area could further investigate the relationships that *multiple* types of infrastructure networks (in addition to road networks) have with emergency response and/or evacuation efforts. Hurricane Harvey provides an example of a situation in which emergency response efforts were hindered due to conditions on another network. The affected road infrastructure was designed so that flood waters gathered and drained in streets rather than near buildings. The resulting high water levels in streets caused unforeseen difficulties in reaching community members that needed emergency medical attention [97]. In addition to physical access challenges, emergency medical services may face complications if patient information is inaccessible to medical personnel due to power network failure or if individuals are unable to contact emergency services due to cellular network failure.

Collaboration between specialized work crews (or requirements for specific types or numbers of work crews on particular tasks) could be explored in future research. For example, power network and road network restoration crews may have to collaborate in order to remove fallen power lines from roadways in a safe manner. Fuel availability for restoration resources as well as disruptions to power supplies also create challenges, resulting in delayed restoration efforts [98]; efficient methods of scheduling coordinated solutions can help minimize the impact of these and similar issues. Experiences in the field

[97] and [98] motivate the need for further investigation of effective decision-making and scheduling methods for post-disaster restoration in interdependent systems. Considering stochasticity in interdependent restoration models would offer new insights. Uncertain elements could include damage levels and locations; availability, location, or capabilities of restoration crews; and the interdependency relationships themselves. Finally, research into the effect of emerging technologies on restoration efforts may significantly increase the efficiency of response and recovery operations. For example, drones have been introduced into the commercial logistics industry for deliveries. Similarly, the benefit of using drones to deliver relief supplies or collect information about damage levels and locations, isolated communities (due to a disaster), or casualties can be examined using mathematical models. Incorporating the capabilities of new technologies into decision-making may lead to the definition of new problems and solution techniques.

5. Conclusion

In this article, we provided an overview of the literature on the allocation of resources to those in need and restoration of infrastructure networks affected by adverse events, such as natural disasters. The efficiency and effectiveness of these decisions can decrease the short- and long-term negative impact of these events on communities. We provided a review of the recent literature on independent systems, presented examples from the relatively limited but growing literature that considers demand, resource, and/or network interdependencies, and suggested potential research directions.

Challenges in decision-making due to interdependencies are abundant, as exhibited in the real-world examples provided in our article. The mathematical and managerial challenges that interdependencies introduce to operations researchers and field agencies are evident. For example, after the September 11, 2001, terrorist attacks on the World Trade Center (WTC), the New York City Office of Emergency Management (OEM) was responsible for coordinating the response actions of approximately 150 organizations. The OEM was headquartered at the WTC, and the attacks resulted in loss of their command center. Failure of telephone, power, and computer systems hindered coordination among response agencies, and police barriers in the area slowed down officials who were attempting to access the site. Further complications included disruption of transportation to Lower Manhattan and evacuation of the nearby Environmental Protection Agency office (an organization that was partly responsible for recovery efforts) [99].

In the aftermath of such extreme events, it is not difficult to imagine the challenges of coordinating search-and-rescue, response (e.g., debris clearance, infrastructure restoration, and resource allocation), and other response and recovery activities. The need for increased efficiency and effectiveness in complex and/or decentralized decision-making environments motivates the development of modeling and solution methods that are efficient, effective, and equitable. Quantitative models for interdependent systems (such as those discussed in this review) can inform and enable planning of coordinated response efforts and increase visibility and cooperation between agencies.

The consideration of interdependencies is crucial while making decisions during mitigation, preparedness, response, and recovery periods of disaster and emergency management. We hope that this review will further spur interest in this research direction.

Acknowledgment

This work was supported in part by NSF Grant CMMI-1538860 and the following Georgia Tech benefactors: W. W. George, A. Laliberte, J. C. Mello, R. “Rick” E. and C. Zalesky, and Claudia and Paul Raines. We are also grateful to Dr. H. Smalley and the anonymous reviewers for their comments and suggestions, which helped to improve the content and exposition of this article.

Arden E. Baxter and Hannah E. Wilborn Lagerman are co-first authors.

References

1. M. Çelik, O. Ergun, B. Johnson, et al., “Humanitarian logistics,” in *Proc. TutORials Oper. Res.*, 2012, pp. 18–49.
2. O. Ergun, G. Karakus, P. Keskinocak, et al., “Operations research to improve disaster supply chain management,” *Encyclopedia Oper. Res. Manage. Sci.*, vol. 6, pp. 3802–3810, 2010.
3. O. Ergun, P. Keskinocak, J. Swann, et al., “Disaster preparedness and retail operations,” in *Handbook of Operations Research for Homeland Security*. New York, NY, USA: Springer, 2012.
4. M. Celik, P. Keskinocak, M. Soldner, et al., “Humanitarian applications of supply chain optimization,” in *Advances and Trends in Optimization with Engineering Applications*. Philadelphia, PA, USA: SIAM, 2016.
5. “Acertainment of the estimated excess mortality from Hurricane Maria in Puerto Rico,” Milken Institute School of Public Health, George Washington Univ., Washington, DC, USA, 2018.
6. P. B. Emmanuel Raju and H. Tehler, “Exploring interdependencies and common goals in disaster recovery coordination,” *Procedia Eng.*, vol. 212, pp. 1002–1009, 2018.
7. E. Raju and P. Becker, “Multi-organisational coordination for disaster recovery: The story of post-tsunami Tamil Nadu, India,” *Int. J. Disaster Risk Reduction*, vol. 4, pp. 82–91, 2013, doi: 10.1016/j.ijdrr.2013.02.004.
8. L. K. Comfort and N. Kapucu, “Inter-organizational coordination in extreme events: The World Trade Center attacks, September 11, 2001,” *Natural Hazards*, vol. 39, no. 2, pp. 309–327, 2006, doi: 10.1007/s11069-006-0030-x.
9. L. Muggy and J. L. Heier Stamm, “Game theory applications in humanitarian operations: A review,” *J. Humanitarian Logistics Supply Chain Manage.*, vol. 4, no. 1, pp. 4–23, 2014, doi: 10.1108/jhlscm-07-2013-0026.
10. D. Seaberg, L. Devine, and J. Zhuang, “A review of game theory applications in natural disaster management research,” *Natural Hazards*, vol. 89, no. 3, pp. 1461–1483, 2017, doi: 10.1007/s11069-017-3033-x.

11. V. Bayram, "Optimization models for large scale network evacuation planning and management: A literature review," *Surv. Oper. Res. Manage. Sci.*, vol. 21, no. 2, pp. 63–84, 2016, doi: 10.1016/j.sorms.2016.11.001.
12. T. M. Alan, T. C. Matiszw, and T. H. Grubesic, "A methodological overview of network vulnerability analysis," *Growth Change*, vol. 39, no. 4, pp. 573–592, 2008.
13. A. T. M. Tony and H. Grubesic, "Vital nodes, interconnected infrastructure, and the geographies of network survivability," *Ann. Assoc. Amer. Geographers*, vol. 96, no. 1, pp. 64–83, 2006.
14. A. Nagurney and Q. Qiang, "Fragile networks: Identifying vulnerabilities and synergies in an uncertain age," *Int. Trans. Oper. Res.*, vol. 19, nos. 1/2, pp. 123–160, 2012, doi: 10.1111/j.1475-3995.2010.00785.x.
15. S. Duran, M. A. Gutierrez, and P. Keskinocak, "Pre-positioning of emergency items for CARE international," *Interfaces*, vol. 41, no. 3, pp. 223–237, 2011, doi: 10.1287/inte.1100.0526.
16. Ç. Renkli and S. Duran, "Pre-positioning disaster response facilities and relief items," *Human Ecological Risk Assessment*, vol. 21, no. 5, pp. 1169–1185, 2015, doi: 10.1080/10807039.2014.957940.
17. B. Balcik and B. M. Beamon, "Facility location in humanitarian relief," *Int. J. Logistics Res. Appl.*, vol. 11, no. 2, pp. 101–121, 2008, doi: 10.1080/13675560701561789.
18. J. Salmerón and A. Apte, "Stochastic optimization for natural disaster asset prepositioning," *Prod. Oper. Manage.*, vol. 19, no. 5, pp. 561–574, 2010, doi: 10.3401/poms.1080.01119.
19. E. J. Lodree, K. N. Ballard, and C. H. Song, "Pre-positioning hurricane supplies in a commercial supply chain," *Socio-Econ. Planning Sci.*, vol. 46, no. 4, pp. 291–305, 2012, doi: 10.1016/j.seps.2012.03.003.
20. C. G. Rawls and M. A. Turnquist, "Pre-positioning of emergency supplies for disaster response," *Transp. Res. B, Methodological*, vol. 44, no. 4, pp. 521–534, 2010, doi: 10.1016/j.trb.2009.08.003.
21. M.-S. Chang, Y.-L. Tseng, and J.-W. Chen, "A scenario planning approach for the flood emergency logistics preparation problem under uncertainty," *Transp. Res. E, Logistics Transp. Rev.*, vol. 43, no. 6, pp. 737–754, 2007, doi: 10.1016/j.tre.2006.10.013.
22. A. K. Chakravarty, "Humanitarian relief chain: Rapid response under uncertainty," *Int. J. Prod. Econ.*, vol. 151, pp. 146–157, 2014, doi: 10.1016/j.ijpe.2013.10.007.
23. A. Bozorgi-Amiri, M. S. Jabalameli, and S. M. J. Mirzapour Al-e-Hashem, "A multi-objective robust stochastic programming model for disaster relief logistics under uncertainty," *OR Spectrum*, vol. 35, no. 4, pp. 905–933, 2011, doi: 10.1007/s00291-011-0268-x.
24. R. Mohammadi, S. M. T. F. Ghomi, and F. Jolai, "Prepositioning emergency earthquake response supplies: A new multi-objective particle swarm optimization algorithm," *Appl. Math. Model.*, vol. 40, nos. 9/10, pp. 5183–5199, 2016, doi: 10.1016/j.apm.2015.10.022.
25. W. Manopiniwes, K. Nagasawa, and T. Irohara, "Humanitarian relief logistics with time restriction: Thai flooding case study," *Ind. Eng. Manage. Syst.*, vol. 13, no. 4, pp. 398–407, 2014, doi: 10.7232/iems.2014.13.4.398.
26. L. B. Davis, F. Samanlioglu, X. Qu, and S. Root, "Inventory planning and coordination in disaster relief efforts," *Int. J. Prod. Econ.*, vol. 141, no. 2, pp. 561–573, 2013, doi: 10.1016/j.ijpe.2012.09.012.
27. S. Duran, O. Ergun, P. Keskinocak, et al., "Humanitarian logistics: Advanced purchasing and pre-positioning of relief items," in *Handbook of Global Logistics: Transportation in International Supply Chains*. New York, NY, USA: Springer, 2012, pp. 447–462.
28. M. Horne, "Hurricane Katrina's devastation in photos," A&E Television Networks, LLC. 2018. [Online]. Available: https://www.history.com/news/hurricane-katrina-photos
29. L. E. De la Torre, I. S. Dolinskaya, and K. R. Smilowitz, "Disaster relief routing: Integrating research and practice," *Socio-Econ. Planning Sci.*, vol. 46, no. 1, pp. 88–97, 2012, doi: 10.1016/j.seps.2011.06.001.
30. V. De Angelis, M. Mecoli, C. Nikoi, et al., "Multiperiod integrated routing and scheduling of world food programme cargo planes in angola," *Comput. Oper. Res.*, vol. 34, no. 6, pp. 1601–1615, 2007, doi: 10.1016/j.cor.2005.07.012.
31. K. Viswanath and S. Peeta, "Multicommodity maximal covering network design problem for planning critical routes for earthquake response," *Transp. Res. Rec., J. Transp. Res. Board*, vol. 1857, no. 1, pp. 1–10, 2003, doi: 10.3141/1857-01.
32. M. Huang, K. Smilowitz, and B. Balcik, "Models for relief routing: Equity, efficiency and efficacy," *Transp. Res., E, Logistics Transp. Rev.*, vol. 48, no. 1, pp. 2–18, 2012, doi: 10.1016/j.tre.2011.05.004.
33. G. Barbarosoğlu and Y. Arda, "A two-stage stochastic programming framework for transportation planning in disaster response," *J. Oper. Res. Soc.*, vol. 55, no. 1, pp. 43–53, 2017, doi: 10.1057/palgrave.jors.2601652.
34. H. O. Mete and Z. B. Zabinsky, "Stochastic optimization of medical supply location and distribution in disaster management," *Int. J. Prod. Econ.*, vol. 126, no. 1, pp. 76–84, 2010, doi: 10.1016/j.ijpe.2009.10.004.
35. A. M. Caunhye, Y. Zhang, M. Li, et al., "A location-routing model for prepositioning and distributing emergency supplies," *Transp. Res. E, Logistics Transp. Rev.*, vol. 90, pp. 161–176, 2016, doi: 10.1016/j.tre.2015.10.011.
36. F. Tricoire, A. Graf, and W. J. Gutjahr, "The bi-objective stochastic covering tour problem," *Comput. Oper. Res.*, vol. 39, no. 7, pp. 1582–1592, Jul. 2012, doi: 10.1016/j.cor.2011.09.009.
37. Z. Shen, M. M. Dessouky, and F. Ordóñez, "A two-stage vehicle routing model for large-scale bioterrorism emergencies," *Networks*, vol. 54, no. 4, pp. 255–269, 2009, doi: 10.1002/net.20337.
38. B. Balcik, B. M. Beamon, and K. Smilowitz, "Last mile distribution in humanitarian relief," *J. Intell. Transp. Syst.*, vol. 12, no. 2, pp. 51–63, 2008, doi: 10.1080/15472450802023329.
39. W. Yi and A. Kumar, "Ant colony optimization for disaster relief operations," *Transp. Res. E, Logistics Transp. Rev.*, vol. 43, no. 6, pp. 660–672, 2007, doi: 10.1016/j.tre.2006.05.004.
40. W. Yi and L. Özdamar, "A dynamic logistics coordination model for evacuation and support in disaster response activities," *Eur. J. Oper. Res.*, vol. 179, no. 3, pp. 1177–1193, 2007, doi: 10.1016/j.ejor.2005.03.077.
41. J.-H. Zhang, J. Li, and Z.-P. Liu, "Multiple-resource and multiple-depot emergency response problem considering secondary disasters," *Expert Syst. Appl.*, vol. 39, no. 12, pp. 11066–11071, 2012, doi: 10.1016/j.eswa.2012.03.016.
42. J. Healy, F. Robles, and R. Nixon, "Aid is getting to Puerto Rico. Distributing it remains a challenge," *New York Times*, 2017. [Online]. Available: https://www.nytimes.com/2017/10/03/us/puerto-rico-aid-fema-maria.html
43. R. Aringhieri, M. E. Bruni, S. Khodaparasti, et al., "Emergency medical services and beyond: Addressing new challenges through a wide literature review," *Comput. Oper. Res.*, vol. 78, pp. 349–368, 2017, doi: 10.1016/j.cor.2016.09.016.
44. M. Reuter-Oppermann, P. L. Van den Berg, and J. L. Vile, "Logistics for emergency medical service systems," *Health Syst.*, vol. 6, no. 3, pp. 187–208, 2017, doi: 10.1057/s41306-017-0023-x.
45. Q. Gong and R. Batta, "Allocation and reallocation of ambulances to casualty clusters in a disaster relief operation," *IIE Trans.*, vol. 39, no. 1, pp. 27–39, 2007, doi: 10.1080/07408170600743938.
46. P. L. Van den Berg and J. T. Van Essen, "Scheduling non-urgent patient transportation while maximizing emergency coverage," *Transp. Sci.*, vol. 5, pp. 319–622, 2019, doi: 10.1287/trsc.2018.0823.
47. S. Yoon and L. A. Albert, "An expected coverage model with a cutoff priority queue," *Health Care Manage. Sci.*, vol. 21, no. 4, pp. 517–533, Dec. 2018, doi: 10.1007/s10729-017-9409-3.
48. A. Karimi, M. Gendreau, and V. Verter, "Performance approximation of emergency service systems with priorities and partial backups," *Transp. Sci.*, vol. 52, no. 5, pp. 1235–1252, 2018, doi: 10.1287/trsc.2017.0810.
49. L. A. McLay, "A maximum expected covering location model with two types of servers," *IIE Trans.*, vol. 41, no. 8, pp. 730–741, 2009, doi: 10.1080/07408170802702138.

50. M. S. Maxwell, M. Restrepo, S. G. Henderson, et al., “Approximate dynamic programming for ambulance redeployment,” *INFORMS J. Comput.*, vol. 22, no. 2, pp. 266–281, 2010, doi: 10.1287/ijoc.1090.0345.
51. A. F. Mills, N. T. Argon, and S. Ziya, “Dynamic distribution of patients to medical facilities in the aftermath of a disaster,” *Oper. Res.*, vol. 66, no. 3, pp. 716–732, 2018, doi: 10.1287/opre.2017.1695.
52. G. Schryen, G. Rauchecker, and T. Comes, “Resource planning in disaster response,” *Bus. Inf. Syst. Eng.*, vol. 57, no. 4, pp. 243–259, 2015, doi: 10.1007/s12599-015-0381-5.
53. F. Wex, G. Schryen, S. Feuerriegel, et al., “Emergency response in natural disaster management: Allocation and scheduling of rescue units,” *Eur. J. Oper. Res.*, vol. 235, no. 3, pp. 697–708, 2014, doi: 10.1016/j.ejor.2013.10.029.
54. A. A. Nasrollahzadeh, A. Khademi, and M. E. Mayorga, “Real-time ambulance dispatching and relocation,” *Manuf. Service Oper. Manage.*, vol. 20, no. 3, pp. 467–480, 2018, doi: 10.1287/msom.2017.0649.
55. G. Rauchecker and G. Schryen, “An exact branch-and-price algorithm for scheduling rescue units during disaster response,” *Eur. J. Oper. Res.*, vol. 272, no. 1, pp. 352–363, 2019, doi: 10.1016/j.ejor.2018.06.010.
56. B. Bodaghi and E. Palaneeswaran, “An optimization model for scheduling emergency operations with multiple teams,” in *Proc. Int. Conf. Ind. Eng. Operations Manage.*, Detroit, MI, USA, 2016, pp. 436–442.
57. N. Altay, “Capability-based resource allocation for effective disaster response,” *IMA J. Manage. Math.*, vol. 24, no. 2, pp. 253–266, 2012, doi: 10.1093/imaman/dps001.
58. Z. Su, G. Zhang, Y. Liu, et al., “Multiple emergency resource allocation for concurrent incidents in natural disasters,” *Int. J. Disaster Risk Reduction*, vol. 17, pp. 199–212, 2016, doi: 10.1016/j.ijdrr.2016.05.003.
59. B. Bodaghi, E. Palaneeswaran, and B. Abbasi, “Bi-objective multi-resource scheduling problem for emergency relief operations,” *Prod. Planning Control*, vol. 29, no. 14, pp. 1191–1206, 2019, doi: 10.1080/09537287.2018.1542026.
60. K. Lee, L. Lei, M. Pinedo, et al., “Operations scheduling with multiple resources and transportation considerations,” *Int. J. Prod. Res.*, vol. 51, nos. 23/24, pp. 7071–7090, 2013, doi: 10.1080/00207543.2013.781283.
61. L. Lei, M. Pinedo, L. Qi, et al., “Personnel scheduling and supplies provisioning in emergency relief operations,” *Ann. Oper. Res.*, vol. 235, no. 1, pp. 487–515, 2015, doi: 10.1007/s10479-015-1990-6.
62. C. Guillote, C. Patrick, K. Schulz, et al., “Preparation, response and lessons learned from Hurricane Harvey,” *J. Emergency Med. Services*, vol. 43, no. 3, 2018.
63. M. Çelik, “Network restoration and recovery in humanitarian operations: Framework, literature review, and research directions,” *Surv. Operations Res. Manage. Sci.*, vol. 21, no. 2, pp. 47–61, 2016, doi: 10.1016/j.sorms.2016.12.001.
64. S. M. Rinaldi, J. P. Peerenboom, and T. K. Kelly, “Identifying, understanding, and analyzing critical infrastructure interdependencies,” *IEEE Control Syst.*, vol. 21, no. 6, pp. 11–25, Dec. 2001, doi: 10.1109/37.969131.
65. K. Govindan, M. Fattahi, and E. Keyvanshokooh, “Supply chain network design under uncertainty: A comprehensive review and future research directions,” *Eur. J. Oper. Res.*, vol. 263, no. 1, pp. 108–141, 2017, doi: 10.1016/j.ejor.2017.04.009.
66. D. Hutchinson and J. P. G. Sterbenz, “Architecture and design for resilient networked systems,” *Comput. Commun.*, vol. 131, pp. 13–21, 2018.
67. D. Tipper, “Resilient network design: Challenges and future directions,” *Telecommun. Syst.*, vol. 56, no. 1, pp. 5–16, 2013, doi: 10.1007/s11235-013-9815-x.
68. M. Tornatore, J. Andre, P. Barbarczi, et al., “A survey on network resiliency methodologies against weather-based disruptions,” in *Proc. 8th Int. Workshop Resilient Netw. Des. Model.*, 2016, pp. 23–34.
69. U. S. D. o. H. Security, “Foundations of Resilience.” [Online]. Available: https://www.dhs.gov/topic/resilience. Accessed on: Jun. 10, 2019.
70. The President’s National Infrastructure Advisory Council, “Surviving a catastrophic power outage,” 2018. [Online]. Available: https://www.dhs.gov/sites/default/files/publications/NIAC%20Catastrophic%20Power%20Outage%20Study_508%20FINAL.pdf
71. K. Engel, T. Kalinowski, and M. W. P. Savelsbergh, “Incremental network design with minimum spanning trees,” *J. Graph Algorithms Appl.*, vol. 21, no. 4, pp. 417–432, 2017.
72. T. Elgindy, A. T. Ernst, M. Baxter, et al., “Incremental network design with shortest paths,” *Eur. J. Oper. Res.*, vol. 238, no. 3, pp. 675–684, 2014.
73. T. Kalinowski, D. Matsypura, and M. W. P. Savelsbergh, “Incremental network design with maximum flows,” *Eur. J. Oper. Res.*, vol. 242, no. 1, pp. 51–62, 2015, doi: 10.1016/j.ejor.2014.10.003.
74. L. Murawski and R. L. Church, “Improving accessibility to rural health services—The maximal covering network improvement problem,” *Socio-Econ. Planning Sci.*, vol. 43, pp. 102–110, 2009, doi: 10.1016/j.seps.20.
75. M. P. Scaparra and R. L. Church, “A GRASP and path relinking heuristic for rural road network development,” *J. Heuristics*, vol. 11, pp. 89–108, 2005.
76. P. A. Maya Duque, S. Coene, P. Goos, et al., “The accessibility arc upgrading problem,” *Eur. J. Oper. Res.*, vol. 224, no. 3, pp. 458–465, 2013, doi: 10.1016/j.ejor.2012.09.005.
77. Q. Meng and H. Yang, “Benefit distribution and equity in road network design,” *Transp. Res., B*, vol. 36, pp. 19–35, 2002.
78. A. Chen and C. Yang, “Stochastic transportation network design problem with spatial equity constraint,” *Transp. Res. Rec., J. Transp. Res. Board*, vol. 1882, pp. 97–104, 2004.
79. S. O. Krumke, M. V. Marathe, H. Noltemeier, et al., “Approximation algorithms for certain network improvement problem,” *J. Combinatorial Optim.*, vol. 2, pp. 257–288, 1998.
80. H. A. Gay, R. Santiago, B. Gil, et al., “Lessons learned from hurricane maria in Puerto Rico: Practical measures to mitigate the impact of a catastrophic natural disaster on radiation oncology patients,” *Practical Radiation Oncol.*, vol. 9, no. 5, pp. 305–321, Sep./Oct. 2019, doi: 10.1016/j.prro.2019.03.007.
81. M. Kasaei and F. S. Salman, “Arc routing problems to restore connectivity of a road network,” *Transp. Res., E, Logistics Transp. Rev.*, vol. 95, pp. 177–206, 2016, doi: 10.1016/j.tre.2016.09.012.
82. P. A. Maya Duque, I. S. Dolinskaya, and K. Sörensen, “Network repair crew scheduling and routing for emergency relief distribution problem,” *Eur. J. Oper. Res.*, vol. 248, no. 1, pp. 272–285, 2016, doi: 10.1016/j.ejor.2015.06.026.
83. V. Akbari and F. S. Salman, “Multi-vehicle prize collecting arc routing for connectivity problem,” *Comput. Oper. Res.*, vol. 82, pp. 52–68, 2017, doi: 10.1016/j.cor.2017.01.007.
84. D. Tuzun Aksu and L. Ozdamar, “A mathematical model for post-disaster road restoration: Enabling accessibility and evacuation,” *Transp. Res., E, Logistics Transp. Rev.*, vol. 61, pp. 56–67, 2014, doi: 10.1016/j.tre.2013.10.009.
85. S. Kim, Y. Shin, G. M. Lee, et al., “Network repair crew scheduling for short-term disasters,” *Appl. Math. Model.*, vol. 64, pp. 510–523, 2018, doi: 10.1016/j.apm.2018.07.047.
86. M. Çelik, Ö. Ergun, and P. Keskinocak, “The post-disaster debris clearance problem under incomplete information,” *Oper. Res.*, vol. 63, no. 1, pp. 65–85, 2015, doi: 10.1287/opre.2014.1342.
87. I. Averbakh, “Minimizing the makespan in multiserver network restoration problems,” *Networks*, vol. 70, no. 1, pp. 60–68, 2017, doi: 10.1002/net.21750.
88. N. Morshedlou, A. D. González, and K. Barker, “Work crew routing problem for infrastructure network restoration,” *Transp. Res., B, Methodological*, vol. 118, pp. 66–89, 2018, doi: 10.1016/j.trb.2018.10.001.
89. A. Ulusan and O. Ergun, “Restoration of services in disrupted infrastructure systems: A network science approach,” *PLoS One*, vol. 13, no. 2, 2018, Art. no. e0192272, doi: 10.1371/journal.pone.0192272.

90. S. Iloglu and L. A. Albert, “An integrated network design and scheduling problem for network recovery and emergency response,” *Oper. Res. Perspectives*, vol. 5, pp. 218–231, 2018, doi: 10.1016/j.orp.2018.08.001.
91. S. G. Nurre, B. Cavdaroglu, J. E. Mitchell, et al., “Restoring infrastructure systems: An integrated network design and scheduling (INDS) problem,” *Eur. J. Oper. Res.*, vol. 223, no. 3, pp. 794–806, 2012, doi: 10.1016/j.ejor.2012.07.010.
92. S. G. Nurre and T. C. Sharkey, “Integrated network design and scheduling problems with parallel identical machines: Complexity results and dispatching rules,” *Networks*, vol. 63, no. 4, pp. 306–326, 2014, doi: 10.1002/net.21547.
93. A. D. González, L. Dueñas-Osorio, M. Sánchez-Silva, et al., “The interdependent network design problem for optimal infrastructure system restoration,” *Comput.-Aided Civil Infrastructure Eng.*, vol. 31, no. 5, pp. 334–350, 2016, doi: 10.1111/mice.12171.
94. B. Cavdaroglu, E. Hammel, J. E. Mitchell, et al., “Integrating restoration and scheduling decisions for disrupted interdependent infrastructure systems,” *Ann. Oper. Res.*, vol. 203, no. 1, pp. 279–294, 2011, doi: 10.1007/s10479-011-0959-3.
95. Y. Almoghathawi, K. Barker, and L. A. Albert, “Resilience-driven restoration model for interdependent infrastructure networks,” *Rel. Eng. Syst. Saf.*, vol. 185, pp. 12–23, 2019, doi: 10.1016/j.ress.2018.12.006.
96. K. Barker, D. B. Karakoc, and Y. Almoghathawi, “Interdependent infrastructure network restoration from a community resilience perspective,” in *Proc. ESREL*, 2018, pp. 1261–1267.
97. NSF, “Better coordination networks to strengthen interdependent infrastructure resilience.” 2018. [Online]. Available: https://www.nsf.gov/discoveries/disc_summ.jsp?cntn_id = 296559&WT.mc_id = USNSF_1. Accessed on: Oct. 5, 2019.
98. J. E. Bigger, M. G. Willingham, F. Krimgold, et al., “Consequences of critical infrastructure interdependencies: lessons from the 2004 hurricane season in Florida,” *Int. J. Crit. Infrastruct.*, vol. 5, no. 3, pp. 199–219, 2009, doi: 10.1504/ijcis.2009.024871.
99. M. A. Crane, N. C. Levy-Carrick, L. Crowley, et al., “The response to September 11: A disaster case study,” *Ann. Global Health*, vol. 80, no. 4, pp. 320–31, Jul./Aug. 2014, doi: 10.1016/j.aogh.2014.08.215.

Received December 14, 2018; accepted for publication October 17, 2019

Arden E. Baxter *Georgia Tech, Atlanta, GA 30332 USA (abaxter@gaetch.edu).* Ms. Baxter received a B.A. degree in mathematics and computer science from Rollins College, Winter Park, FL, USA, in 2018. She is currently working toward the Ph.D. degree in the School of Industrial and Systems Engineering, Georgia Tech, Atlanta, GA, USA. She is also a Student Affiliate in the Center for Health and Humanitarian Systems, Georgia Tech. She is a 2019 NSF Graduate Research Fellow. She is also a member of INFORMS and the Social Chair for the Georgia Tech INFORMS Student Chapter.

Hannah E. Wilborn Lagerman *Georgia Tech, Atlanta, GA 30332 USA (hannah.lagerman@gatech.edu).* Ms. Wilborn Lagerman received a B.S. degree in industrial engineering from Kansas State University, Manhattan, KS, USA, in 2018. She is currently working toward the Ph.D. degree in the School of Industrial and Systems Engineering, Georgia Tech, Atlanta, GA, USA. She is currently a Student Affiliate in the Center for Health and Humanitarian Systems, Georgia Tech. She held positions with Siemens Wind Power and Walmart Logistics Engineering prior to beginning graduate study at Georgia Tech. She is a member of INFORMS and the Secretary for the Georgia Tech INFORMS Student Chapter.

Pinar Kesinocak *Georgia Tech, Atlanta, GA 30332 USA (pinar@gatech.edu).* Dr. Keskinocak received B.S. and M.S. degrees in industrial engineering from Bilkent University, Ankara, Turkey, in 1991 and 1992, respectively, and M.S. and Ph.D. degrees in operations research from Carnegie Mellon University, Pittsburgh, PA, USA, in 1994 and 1997, respectively. She is the William W. George Chair and Professor with the School of Industrial and Systems Engineering and the Director of the Center for Health and Humanitarian Systems, Georgia Tech, Atlanta, GA, USA. Prior to joining Georgia Tech in 1999, she worked with IBM T.J. Watson Research Center. She is an INFORMS Fellow and is currently the President-elect of INFORMS. Previously, she served as a Secretary and as the Vice President of Membership and Professional Recognition on the INFORMS board. She has served in various editorial roles, including as a Department Editor for *Operations Research, IISE Transactions on Healthcare Systems Engineering*, and *Service Science*, and on the editorial boards of *Management Science*, *Manufacturing and Service Operations Management*, *IIE Transactions*, and *Production and Operations Management*. She is a member of INFORMS and IISE.