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Stochastic Optimization of Large-Scale Patient Evacuation Before Hurricanes

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Abstract

The total cost for weather-related disasters in the US increases over time, and hurricanes usually create the most damage. One of the challenges, which is present in almost every major hurricane event, is the patient evacuation mission. We propose a comprehensive modeling and methodological framework for a large-scale patient evacuation problem when an area is faced with a forecasted disaster such as a hurricane. In this work, we integrate a hurricane scenario generation scheme using publicly available surge level forecasting software and a scenario-based stochastic integer program to make decisions on patient movements, staging area locations and positioning of emergency medical vehicles with an objective of minimizing the total expected cost of evacuation and the setup cost of staging areas. The hurricane scenario generation scheme incorporates the uncertainties in the hurricane intensity, direction, forward speed and tide level. To demonstrate the modeling approach, we apply real-world data from the Southeast Texas region in our experiments. We highlight the importance of operation time limits, the number of available resources and an accurate forecast on forthcoming hurricanes in determining the locations of staging areas and patient evacuation decisions.

Keywords
Patient evacuation, stochastic programming, hurricanes, mixed integer programming, evacuation planning

1. Introduction
In 2017, the total cost for weather-related disasters in the US was $306 billion, and three major hurricanes contributed more than 85% of the total bill: Hurricane Harvey $125 billion, Hurricane Maria $90 billion and Hurricane Irma $50 billion [6]. The data clearly implies that the total cost for natural disasters increases over time, thus, we must plan ahead for possible implications from increased threats from hurricanes. In preparing for future hurricanes and other disasters, federal, state and local agencies engage in multiple joint efforts. Typically, this involves making plans for resource mobilization, involving the safety of millions of citizens. These activities include pre-positioning emergency supplies, making evacuation plans if necessary, opening and operating shelters, rescuing stranded people and animals, and of course rebuilding in the aftermath. In this research, we focus our attention patient evacuation, which is present in almost every major hurricane event.

In Texas, there are 22 Regional Advisory Councils (RAC), and the SouthEast Texas Regional Advisory Council (SETRAC) provides collaborative planning and response to emergencies in the southeast region of Texas with 180 hospitals in 25 counties. As a nonprofit organization that seek to save lives and improve health outcomes, one of the objectives of SETRAC in hurricane events is to evacuate patients from healthcare facilities in the areas threatened by the hurricane to facilities in safe zones. During Hurricane Harvey in 2017, SETRAC coordinated 773 patient movement missions that evacuated 1,544 patients from 24 hospitals. In this article, we propose a two-stage stochastic mixed integer programming framework for patient evacuation which determines the location of resource staging areas in the first stage, and ambulance routing assignments as a recourse, while minimizing the expected total cost of patient evacuation operations.

The remainder of this paper is organized as follows. Section 2 reviews the relevant work and recent literature that discusses patient evacuation operations and resource allocation before hurricanes. In Section 3, we introduce modeling assumptions and present the stochastic integer programming formulation. Section 4 provides the experimental setup and summarizes the preliminary results. We conclude with results and provide future research directions in Section 5.

2. Related Literature
2.1 Deterministic evacuation and inventory optimization model
Balcik et al. [1] survey various inventory management models during pre-disaster and post-disaster stages and highlight several problem aspects such as multiple items, capacitated facilities, variable lead times and different cost

items in inventory management models that should be further examined. A survey by Bayram [3] provides a rather comprehensive review of evacuation planning and management literature, citing papers focusing on static/dynamic, deterministic/stochastic/robust evacuation modeling with a focus on network and traffic assignment methods. Seeing the extensive body of work on general population evacuation (assuming wide availability of means of transportation for all), the review calls for focused research on evacuation of people with special needs (utilizing centrally controlled means of transportation such as mass-transit or multi-modal transportation resources), as in our case. For a single hospital evacuation, Tayfur and Taaffe [10] propose a deterministic mixed integer linear programming transportation planning model for identifying the staff and vehicle transport requirements for evacuating patients within a pre-specified evacuation time while minimizing cost. In other studies, they use a simulation approach to determine the time required to evacuate patients from a hospital [9]. While most of patient evacuation planning, and hence the related research, deals with the problem before the actual disaster, there are a few papers that model the problem of transporting injured people after the disaster. For example, Na and Banerjee [4, 5] develop a deterministic mixed integer model called the Triage Assignment Transportation (TAT) model that determines the post-disaster assignments of vehicles to injured patients, in order to allocate and transport them to multiple hospitals and also supply medical personnel to hospitals with sufficient capacity. The model's composite objective seeks to minimize the total costs of medical procedures, medical resources, and transportation. The complexities of the model emerge from the levels of injuries, the capacities of vehicles, and availability of resources at hospitals.

2.2 Stochastic evacuation and inventory optimization model

Tayfur and Taaffe develop a simulation-optimization hospital evacuation model incorporating the probabilistic nature of disasters [11]. Their stochastic model examines the transport requirements for evacuation while minimizing the total cost within a pre-specified evacuation completion time. Paul and MacDonald [8] introduce a stochastic modeling framework in determining the location and capacities of distribution centers for emergency stockpiles to improve preparedness and develop an evolutionary optimization heuristic. Although the uncertainties in facility damage and casualty losses from disaster is captured as a function of the magnitude of the earthquake, they imply that a more thorough investigation on accurate estimation of probability distribution functions is necessary. Bish et al. [2] introduce an integer programming formulation with the objective of minimizing the expected threat risk (due to the event) and the transportation risk (due to the criticality of the patient). This single evacuating hospital multi-period model determines the allocation of patients with respect to criticality, care requirements, receiving hospital capacities, and vehicle and medical capabilities.

To our knowledge, Pacheco and Batta [7] is the only study that explicitly takes into account updates in the forecasts as a hurricane gets closer to landfall and addresses the optimum timing of making decisions, not for patient evacuation, but for positioning of relief supplies. While location, the capacity of distribution centers, and the evacuation of multiple patient from multiple hospitals under uncertain events are considered in different studies, to the best of our knowledge, no studies have considered providing a solution to the problem combining these attributes. We further distinguish our work by utilizing a commercial weather forecasting model in generating hurricane scenarios to provide a more pragmatic solution to the problem.

3. Model Formulation

To ensure a successful evacuation operation prior to an emerging hurricane, SETRAC determines the staging area locations for emergency medical service (EMS) vehicles and then decides destinations (safe hospitals) for patients being evacuated from hospitals estimated to be affected from the hurricane. The evacuation operation takes place before the storm makes landfall, and with latest available hurricane forecasts, SETRAC strives to make the best decisions. To capture both the uncertainty in weather forecasts while optimizing evacuation decisions, we integrate two parts to construct the patient evacuation model. First, we generate scenarios by utilizing the publicly available state-of-the-art storm surge prediction model called the Sea, Lake, Ocean and Overland Surge for Hurricanes (SLOSH). Then, using the generated scenarios as input, we formulate the stochastic mixed integer optimization model. The objective of the model is to minimize the expected total evacuation cost across all potential hurricane scenarios.

3.1 Scenario Generation

The SLOSH model outputs predicted storm surge levels for the Texas coastal region by taking three attributes as input: the storm category, the direction and the forward speed-tide level pair. We start generating scenarios by combining these three attributes. For each scenario, characterized by the three attributes, we find the storm surge level for the coastal region, and with a certain threshold water depth, we create an inundation map that depicts areas above the threshold depth. Then, with the height above the nearest drainage (HAND) elevation data of each hospital, if the hospital's HAND elevation is below the threshold depth, we assume that the hospital will be flooded. If a hospital is flooded, the demand of the hospital is incurred. The realization of hospital demand depends on the surge profile of each scenario. We assume that the probability distributions for the three attributes are independent, and the probability of each scenario is determined by multiplying the probabilities of the storm category, direction and forward speed-tide pair.

3.2 Evacuation Model Description and Assumptions

Taking the scenarios as input, we now formulate the stochastic mixed integer programming model. First, we assume that the location and availability of the potential receiving hospitals are known. Since SETRAC surveys available bed counts of the potential receiving hospitals a few days before a forecasted hurricane makes landfall, we assume that the receiving hospital availability and locations are deterministic. Another assumption on the receiving hospitals is that they are located in hurricane-safe regions and cannot be damaged or closed by the hurricane. Therefore, all the receiving hospitals are potential destinations for evacuating hospitals in each scenario. There are two types of patients from evacuating hospitals: critical and non-critical. Among all patients, we define critical patients as those who need special care or require individual treatment, and the rest as non-critical patients. For patient evacuation missions, two types of EMS vehicles are used: ambulances and AmBuses. We assume that each ambulance carries one critical or non-critical patient while AmBuses can carry up to 20 non-critical patients at once. The model determines the optimal number of patients that each AmBus should carry. To determine the optimal number of patients to transport in AmBuses, we define the vehicle capacity parameter α^v, and 20 "types" of AmBus, for carrying one patient to 20 patients. To make distinction between ambulances and AmBuses, we set $v = 0$ for ambulances and $v = \{1, \dots 20\}$ for AmBuses. For example, AmBus Type 1 carries 1 patient ($\alpha^1 = 1$) while AmBus Type 10 carries 10 patients ($\alpha^{10} = 10$). Note that $\alpha^0 = 1$ indicates that an ambulance carries only one patient at a time. The disadvantages of AmBuses are that they are slow, and the operational cost is greater, when compared to ambulances. We set the average speed of an AmBus to be one third slower than the ambulances and the operating cost of AmBuses to be three times greater. Loading patients on an AmBus also takes time, and therefore, we add additional loading time in the routes between the evacuating hospitals and the receiving hospitals (T_{jk}^v). The loading time increases by 6 minutes per patient. If an AmBus carries 20 patients, the additional loading time is 120 minutes. We further assume that the ambulances can evacuate both critical and non-critical patients while AmBuses only transport non-critical patients. All the dispatched vehicles must return to staging areas after they complete their missions. Since the vehicles return empty, we drop the patient type index p in the decision variable describing the number of returning EMS vehicles.

3.3 Notation and Formulation

In this section, we describe index sets, parameters and decision variables, and further provide model formulation. All the cost parameters have dollars as the unit of measure, whereas times are in minutes.

Index Sets and Parameters

I	Set of potential staging area locations, indexed by i
J	Set of evacuating hospitals, indexed by j
K	Set of potential receiving hospitals, indexed by k
V	Set of vehicle types (to determine the number of patients carried by AmBuses), indexed by v
P	Set of patient types, {N,C} (non-critical=N, critical=C), indexed by p
S	Set of scenarios, indexed by s
c_{ij}^v	Cost of evacuating a patient from staging area i to evacuating hospital j by vehicle v
c_{jk}^v	Cost of evacuating a patient from evacuating hospital j to receiving hospital k by vehicle v
c_{ki}^v	Cost of evacuating a patient from receiving hospital k to staging area i by vehicle v
T_{ij}^v	Travel time from i to j by vehicle v
T_{jk}^v	Travel time from j to k by vehicle v
T_{ki}^v	Travel time from k to i by vehicle v
D_j^{ps}	Demand of hospital j for patient type p in scenario s
B_k^p	Capacity of receiving hospital k for patient type p
α^v	Capacity of vehicle v
M	A big number
Q_{min}	Minimum number of EMS vehicles needed to open a staging area
T_{max}	Maximum operating time
O_{max}	Maximum number of AmBuses

p^s Probability of scenario s

f_i Cost of opening a staging area at location i

Decision Variables

x_{ij}^{vps} Number of type v EMS vehicles assigned from i to j for transporting type p patients in scenario s

x_{jk}^{vps} Number of type v EMS vehicles assigned from j to k for transporting type p patients in scenario s

x_{ki}^{vs} Number of type v EMS vehicles assigned from k to i in scenario s

z_i 1, if a staging area is located at i; 0 otherwise

u_{ij}^{vs} 1, if a type v EMS vehicle is assigned from i to j in scenario s; 0, otherwise

u_{jk}^{vs} 1, if a type v EMS vehicle is assigned from j to k in scenario s; 0, otherwise

u_{ki}^{vs} 1, if a type v EMS vehicle is assigned from k to i in scenario s; 0, otherwise

q_i^v Number of type v vehicles stationed at staging area i

Model

$$\text{Minimize} \quad \sum_i f_i z_i + \sum_s p^s \left[\sum_{i,j,v,p} c_{ij}^v x_{ij}^{vps} + \sum_{j,k,v,p} c_{jk}^v x_{jk}^{vps} + \sum_{k,i,v} c_{ki}^v x_{ki}^{vs} \right] \tag{1}$$

$$\text{Subject to} \quad \sum_k \alpha^0 x_{jk}^{0,C,s} = D_j^{C,s} \qquad \forall j \in J, s \in S \tag{2}$$

$$\sum_{v,k} \alpha^v x_{jk}^{v,N,s} = D_j^{N,s} \qquad \forall j \in J, s \in S \tag{3}$$

$$\sum_{j,v} \alpha^v x_{jk}^{vps} \le B_k^p \qquad \forall k \in K, p \in P, s \in S \tag{4}$$

$$\sum_{j,p} x_{ij}^{vps} \le q_i^v \qquad \forall i \in I, v \in V, s \in S \tag{5}$$

$$\sum_i x_{ij}^{vps} = \sum_k x_{jk}^{vps} \qquad \forall j \in J, v \in V, p \in P, s \in S \tag{6}$$

$$\sum_{j,p} x_{jk}^{vps} = \sum_i x_{ki}^{vs} \qquad \forall k \in K, v \in V, s \in S \tag{7}$$

$$\sum_{i,v \neq 0} q_i^v \le O_{max} \tag{8}$$

$$x_{ij}^{vps} \le M z_i \qquad \forall i \in I, j \in J, v \in V, p \in P, s \in S \tag{9}$$

$$x_{ki}^{vs} \le M z_i \qquad \forall i \in I, k \in K, v \in V, s \in S \tag{10}$$

$$Q_{min} z_i \le \sum_v q_i^v \qquad \forall i \in I \tag{11}$$

$$x_{ij}^{vps} \le M u_{ij}^{vs} \qquad \forall i \in I, j \in J, v \in V, p \in P, s \in S \tag{12}$$

$$x_{jk}^{vps} \le M u_{jk}^{vs} \qquad \forall j \in J, k \in K, v \in V, p \in P, s \in S \tag{13}$$

$$x_{ki}^{vs} \le M u_{ki}^{vs} \qquad \forall k \in K, i \in I, v \in V, s \in S \tag{14}$$

$$T_{ij}^v u_{ij}^{vs} + T_{jk}^v u_{jk}^{vs} + T_{ki}^v u_{ki}^{vs} \le T_{max} \qquad \forall i \in I, j \in J, k \in K, v \in V, s \in S \tag{15}$$

$$x_{ij}^{vps}, x_{jk}^{vps}, x_{ki}^{vs} \in \mathbb{Z}^+ \qquad \forall i \in I, j \in J, k \in K, v \in V, p \in P, s \in S \tag{16}$$

$$u_{ij}^{vs}, u_{jk}^{vs}, u_{ki}^{vs} \in \{0,1\} \qquad \forall i \in I, j \in J, k \in K, v \in V, s \in S \tag{17}$$

$$z_i \in \{0,1\} \qquad \forall i \in I \tag{18}$$

The objective function (1) minimizes the total expected evacuation cost and the setup cost of staging areas. Constraint (2) ensures that the critical patients are only evacuated by ambulances. In Constraint (3), we allow the non-critical patients to be evacuated by all vehicle types. Constraint (4) restricts the number and type of patients evacuated to receiving hospitals. q_i^v in Constraint (5) is an auxiliary variable that determines the number and type of EMS vehicles stationed at staging area locations. Constraints (6) and (7) are the flow balance constraints that ensure the EMS vehicles that arrive to evacuating hospitals depart from them to carry patients to receiving hospitals and all the EMS vehicles that depart from staging areas eventually return to the staging areas. The maximum number of AmBuses is set by Constraint (8). Constraints (9) and (10) ensure that a staging area must be opened if there is a flow in or out of the staging area. Constraint (11) sets the minimum number of vehicles to open a staging area location. Constraint (12), (13) and (14) define the binary variables u that are used to set the operating time limit in Constraint (15).

4. Preliminary Computational Results

4.1 Experimental Setup

We design our experiments with 4 potential staging areas, 111 evacuating hospitals and 20 receiving hospitals in SETRAC's region, as shown in Figure 1. For the hospital location data, we use the publicly available hospital listings from the Department of Homeland Security website. Among the hospitals in the region monitored by SETRAC, we pick 20 hospitals inland and set them as receiving hospitals. 111 hospitals both inland and in the coastal area are set as evacuating hospitals. The staging area locations are strategically picked within the region. The average speed for an ambulance is 45 mph and for an AmBus is 30 mph. We define the unit operating costs of an ambulance and AmBus as \$90 and \$270 per hour, respectively. The opening cost of a staging area is \$9,000, the maximum operating time is 480 minutes, and the minimum number of vehicles to open a staging area is 50. To make the situation similar to the SETRAC operation during Hurricane Harvey, we set the expected demand (total number of patients to move) to approximately 1,000. About 5% of all patients are classified as critical. Moreover, we define the maximum number of AmBuses as 16. We do not assign a limit on the number of ambulances because mobilization of ambulances is easier, and we want to satisfy all the demand.

Figure 1 The SETRAC region considered in the experiments

We define three hurricane landfall cases. In the first case, which we define as the worst case, we assume that a Category 5 hurricane is expected to make landfall. Assuming that the storm may approach in five directions with three different forward speed-tide pairs, we create 15 scenarios for the worst case. In Case 2, we assume that a storm makes landfall with equal probability as either a Category 4 or 5 storm in five directions with three forward speed-tide pairs. There are 30 scenarios in Case 2. Similarly, in Case 3, we generate 45 scenarios with three storm intensities – Category 3, 4, and 5 – with a uniform distribution, five directions and three forward speed-tide pairs. To generate the probability distribution of storm direction, we imported the weather forecast for Hurricane Harvey in 2017. Using the weather forecast 3 days before the landfall, the probabilities of hurricane approaching in north, north-northwest, northwest, west-northwest and west are 0.05, 0.2, 0.5, 0.2, 0.05 respectively. We finally assume that the forward speed-tide pairs have a uniform distribution. The model is programmed with Pyomo and solved with Gurobi.

4.2 Preliminary Results

We ran the model several times to understand how the expected total cost and the number of staging areas were affected by the number of AmBuses and the maximum operating time in the three cases as presented in Table 1. As expected, the expected total cost in the worst case is the highest among the three cases. Also, the addition of AmBuses decreases the expected total cost. This result is somewhat intuitive because we expect some savings from the batching effect of operating AmBuses. We also observe that the number of staging areas changes as we decrease the maximum operating time. In Case 3, when T_{max} is 480, all the vehicles are at one staging area. However, when we decrease T_{max} to 300, the model opens up two staging areas. Interestingly, all the vehicles begin their trip from one staging area but all the AmBuses return to one of the two staging areas and the ambulances to the other. When we further decrease T_{max} to 240, the model opens only one staging area. Although the resulting staging area locations in $T_{max} = 240$ and 480 are the same, the utilization of the AmBuses is different. When T_{max} is 480, all 16 AmBuses are filled up to the capacity limit of 20. However, when T_{max} is 240, some of the AmBuses transport patients with some seats unfilled because of the patient loading time.

Table 1. Experimental Results

T_{max}	# of AmBuses	Case 1		Case 2		Case 3	
		Expected Total Cost	# of Staging Areas	Expected Total Cost	# of Staging Areas	Expected Total Cost	# of Staging Areas
480	0	247,491	1	235,988	1	226,753	1
480	2	236,647	1	225,145	1	215,909	1
480	16	164,258	1	152,816	1	143,602	1
300	0	247,491	1	235,988	1	226,753	1
300	2	242,335	1	230,850	1	230,832	1
300	16	193,812	2	182,310	2	173,074	2
240	0	247,491	1	235,988	1	226,753	1
240	2	244,301	1	233,082	1	223,930	1
240	16	224,891	1	215,241	1	208,512	1

5. Conclusions and Future Work

In this paper, we develop a two-stage evacuation and allocation model that determines the optimal location of staging areas and number of EMS vehicles in the first stage and the evacuation routes for different types of patients before hurricane as recourse. As the expected total cost diminishes for less significant hurricanes, increasing the number of AmBuses also reduces the expected total cost. Moreover, the restriction of operating time is closely related to both resource and location decisions.

We are extending this model to allow multiple trips of EMS vehicles. Time permitting, the EMS vehicles would make multiple trips between the evacuating and receiving hospitals before reaching the maximum operating time. Also, since the funding for disaster management such as hurricane evacuation might be flexible, we would alternatively approach the problem with an objective of minimizing the expected makespan (total time to evacuate all the patients). Availability and mobilization time of the EMS vehicles are also important factors in making the evacuation decision. As we have seen in the previous section, the operating time limit is also an important factor. Since it is likely that the road network will become congested as a hurricane approaches, we should take the congestion effect into consideration and the timing of patient evacuation. One important area that requires further investigation is scenario generation. Since the SLOSH model mostly predicts the surge level of coastal locations, it is essential to incorporate another model that makes hydrologic forecast for inland locations.

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