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A Large-Scale Patient Evacuation Modeling Framework using Scenario Generation and Stochastic Optimization

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Abstract

This paper proposes a two-stage stochastic mixed integer programming framework for patient evacuation. While minimizing the expected total cost of patient evacuation operations, the model determines the location of staging areas and the number of emergency medical service (EMS) vehicles to mobilize in the first stage, and the EMS vehicle routing assignments in the second stage. A real-world data from Southeast Texas region is used to demonstrate our modeling approach. To provide a more pragmatic solution to the patient evacuation problem, we attempt to create comprehensive hurricane instances by integrating the publicly available state-of-art hydrology models for surge, Sea, Lake Ocean and Overland Surge for Hurricanes (SLOSH), and for streamflow, National Water Model (NWM), prediction. The surge product captures potential flooding in coastal region while the streamflow product predicts inland flooding. The results exhibit the importance of the integrated approach in patient evacuation planning, provide guidance on flood mapping and prove the potential benefit of comprehensive approach in scenario generation.

Keywords
Patient Evacuation, humanitarian logistics, hurricanes, stochastic programming, scenario generation

1. Introduction
Preparing for hurricane and other natural disasters involves making plans for resource mobilization such as pre-positioning emergency supplies, planning evacuation routes, positioning shelters, conducting search-and-rescue missions for stranded people. In this research, we focus our attention to the activities involved in hospital patient evacuation missions.

In Texas, patient evacuation missions during Hurricane Harvey in 2017 was led by the SouthEast Texas Regional Advisory Council (SETRAC). Before the hurricane made landfall, they decided the staging area location near Houston for emergency medical service (EMS) vehicles and crews and coordinated evacuation of 20 hospitals and 25 nursing homes. During Hurricane Ike in 2008, which was a more powerful hurricane than Harvey, SETRAC evacuated 56 hospitals and 200 nursing homes. Motivated by the work of SETRAC in patient evacuation, we propose a two-stage stochastic mixed integer programming framework for patient evacuation. While minimizing the expected total cost of patient evacuation operations, the model determines the location of staging areas and the number of EMS vehicles to mobilize in the first stage, and the EMS vehicle routing assignments in the second stage. To provide a more pragmatic solution to the patient evacuation problem, we exploit the publicly available state-of-art hydrology models to create comprehensive hurricane instances.

2. Related Literature
Balcik et al. [1] provide a survey of various inventory management models during pre-disaster and post-disaster stages. They assert that several problem aspects such as multiple items, capacitated facilities and different cost items in inventory management models should be further examined. A comprehensive review by Bayram [2] surveys evacuation planning and management literature with a focus on network and traffic assignment methods. The author calls for a need in research on evacuation for people in special need by utilizing centrally controlled means of transportation. Tayfur and Taaffe [3] propose a deterministic mixed integer linear programming transportation

planning model for a single hospital evacuation. While minimizing cost, the model identifies the staff and vehicle transport requirements for evacuating patients within a pre-specified evacuation time. Tayfur and Taaffe continue to develop a simulation-optimization hospital evacuation model embodying the uncertainty in natural disaster [4]. While minimizing the total cost within a pre-specific evacuation completion time, their stochastic model studies the transport requirements for evacuation. To improve preparedness in emergency stockpiles, Paul and MacDonald [5] develop a stochastic modeling framework to decide the location and capacities of distribution centers. They use the magnitude of earthquake to capture the uncertainties in facility damage and casualty losses in disasters and acknowledge the need for more accurate estimation method for developing the probability distribution functions.

Paul and Zhang [6] develop a two-stage stochastic programming model with recourse action for optimizing the locations of distribution, medical supply level, and transportation capacity in the first stage and the transportation decisions in the second stage. They generate a finite number of scenarios with the forecast of wind speed distribution and the supply demand is realized based on the distance from the landfall, damage level, and the wind speed. Aslan and Celik [7] also design a two-stage stochastic program, where pre-disaster decision of warehouse location and item pre-positioning are subject to uncertainties in relief item demand and facility vulnerability following the disaster. In their study, the uncertainty on demand and damages on facilities is modeled in terms of continuous probability distributions. Pacheco and Batta [8] explicitly take into account of updates in the forecasts as a hurricane gets closer to landfall and address the optimum timing of making decisions, not for patient evacuation, but for positioning of relief supplies. Kim et al. [9] provide a two-stage stochastic optimization model for patient evacuation before hurricane. Their approach seeks to provide a solution to the problem combining location, the capacity of distribution centers, and the evacuation of multiple patient from multiple hospitals under uncertain hurricane events by incorporating the publicly available storm surge forecasting model. Their approach of generating hurricane scenarios with attributes for storm surge has limitation in generating comprehensive flood maps because the storm surge scenarios focus coastal region and ignores the potential flooding in inland locations. In this study, we reinforce their idea of hurricane scenario generation by incorporating hospitals in both inland and coastal region.

3. Model Formulation

3.1 Scenario Generation

In this paper, we improve the previous scenario generation approach of Kim et al. [9] by generating flood maps caused by both rainfall and storm surge. Kim et al. [9] use SLOSH to generate flood scenarios caused by storm surges. Three parameters, the Saffir-Simpson Hurricane Wind Scale, known as Category 1 to 5 ratings, landfall directions, and forward speed-tide level pairs, characterize each hurricane scenario, and the probability distributions of these parameters are considered independently.

The downside of their approach is that using only the surge product to generate flood maps ignores the potential flood on the inland locations caused by rainfall. To enhance the flood mapping for freshwater flooding, we utilize NWM [10] which calculates the water discharge in volume per unit time for 2.7 million river reaches over the continental US. NWM is a physical modeling framework that utilizes dynamic weather prediction to simulate the streamflow. There are three types of forecast products – short-range, medium-range, and long-range, and we use the medium-range forecast which generates 10-day streamflow predictions in every 3 hours. We collect the NWM forecasts during Hurricane Harvey and use them to produce potential flood maps. We only consider the maximum of the time series data because, in flood mapping, we are interested in the maximum flood height. For example, the first NWM forecast for Hurricane Harvey provides time series of streamflow from August 19, 00:00 to August 29, 00:00 UTC, and the maximum streamflow over this period for a given corresponding watershed is recorded for further calculation of flood height.

To generate flood maps, we convert the streamflow (m^3/s) into stage heights (m), which represent the height of water in meters at the stream reaches, with corresponding rating curves [11]. A rating curve is a graph of streamflow versus water height for a point on a stream and depends of the shape of the river channel. After calculating the stage heights, we subtract the heights with the Height Above Nearest Drainage (HAND) [12] which is the relative elevation of a given point above the nearest drainage. An inundation map depicts areas above a threshold water depth. Each NWM streamflow forecast is combined with a single surge forecast. We obtain the surge output generated by SLOSH with three attributes: the hurricane intensity, the landfall direction and the forward speed-tide level pair. Similar to the method of generating the flood maps with NWM, we create a surge flood map that depicts areas above the threshold depth. If the flood height of the hospital is above threshold depth, we consider the location will be flooded. Then, we form a union of the flooded locations by NWM and SLOSH and incur the demands of the flooded hospitals.

3.2 Evacuation Model Description and Assumptions

In the two-stage stochastic optimization model, the location and availability of potential receiving hospitals are deterministic and known beforehand. We also assume that the receiving hospitals are safe from hurricanes and cannot be damaged or closed by the hurricane. We define two types of patients from evacuating hospitals: critical and non-critical. There are two types of EMS vehicles: ambulances and AmBuses. AmBuses can only evacuate non-critical patients while ambulances can carry both types of patients. The AmBuses carry up to 20 patients while ambulances carry 1 patient. The AmBuses are costly and slower than ambulances. The average speed of an AmBus is one third slower than the ambulance and the operating cost is three times greater. Loading patients on AmBuses take extra 6 minutes per patient. For example, if an AmBus carries 10 patients, an extra loading time of 60 minutes is added to its travel time. All the vehicles start their route at staging areas and return to staging area after they complete their missions.

3.3 Notations and Formulation

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
J	Set of evacuating hospitals
K	Set of potential receiving hospitals
V	Set of vehicle types (to determine the number of patients carried by AmBuses)
P	Set of patient types, {N, C} (non-critical=N, critical=C)
S	Set of scenarios
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
c_v	Cost of operating an EMS 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

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

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

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

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

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

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

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

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

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

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

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

$$q_i^v \le M z_i \qquad \forall i \in I, v \in V \tag{12}$$

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

$$x_{jk}^{vps} \le M u_{jk}^{vs} \qquad \forall j \in J, k \in K, v \in V, p \in P, s \in S \tag{14}$$

$$x_{ki}^{vs} \le M u_{ki}^{vs} \qquad \forall k \in K, i \in I, v \in V, s \in S \tag{15}$$

$$T_{ij}^v u_{ij}^{vs} + T_{jk}^v u_{jk}^{vs} + T_{ki}^v u_{ki}^{vs} \le T_{max} \qquad \forall i \in I, j \in J, k \in K, v \in V, s \in S \tag{16}$$

$$x_{ij}^{vps}, x_{jk}^{vps}, x_{ki}^{vs} \ge 0 \tag{17}$$

$$u_{ij}^{vs}, u_{jk}^{vs}, u_{ki}^{vs} \in \{0,1\} \tag{18}$$

$$z_i \in \{0,1\} \tag{19}$$

The objective of the model is to minimize the total expected evacuation cost, resource cost and setup cost of staging areas (1). Demand for critical and non-critical patients are satisfied by Constraints (2) and (3). We impose the capacity constraints of receiving hospitals with Constraint (4). Constraint (5) determines the number and type of EMS vehicles stationed at staging area locations, i. The EMS vehicles flows from staging areas to evacuating hospitals to receiving hospitals are balanced with Constraint (6) and (7). Constraint (8) imposes the maximum number of AmBuses. Constraint (9) and (10) ensure to open the staging areas with an incoming or outcoming flow. Constraint (11) sets the minimum number of vehicle requirement for opening a staging area, and Constraint (12) makes sure that vehicles are stationed at opened staging areas. The binary variables, u, for determining the operating time limit in constraint (16) are defined in Constraint (13), (14) and (15).

4. Computational Results

4.1 Experiment Setting

We focus on the 108 evacuating hospitals and 20 receiving hospitals in SETRAC's region, and these locations are obtained from the publicly available hospital listings from The Department of Homeland Security websites. The 5 staging area locations are strategically picked within the region. We define the average speed for the two types of vehicles, AmBus and ambulance, as 30 mph and 45 mph respectively. The cost of opening a staging area is \$9,000, and operating costs AmBuses and ambulances are \$270 and \$90 per hour per vehicle. The maximum operating time is 8 hours, and the minimum number of vehicles to open a staging area is 50. Among the patients, about 5% are considered as critical patients. There is no limit on the number of ambulances while we limit the number of AmBuses to 16. It is because there is an actual limit on the number of AmBuses while mobilizing ambulances are relatively easy.

Using the Hurricane Harvey as our experiment hurricane setting, we first define the flooding period as August 26, 00:00 to August 29, 00:00 UTC. Since SETRAC needs to make the evacuation decision 48 hours prior to the landfall, the deadline for the evacuation decision is August 24, 00:00 UTC. With the decision deadline in mind, we collect the medium-range forecast of NWM from August 19, 00:00 to August 23, 18:00 UTC, which gives us 20 NWM streamflow forecasts. The starting date of the NWM forecast is determined as of August 19, 00:00 because its forecast includes the time-series output until August 29, 00:00 UTC. Each NWM forecast is considered as a potential hurricane scenario. To combine the impact of river flooding and coastal flooding, each NWM streamflow forecast is combined with a SLOSH forecast. We obtain the surge forecast generated by SLOSH with the hurricane Advisory 13, which was issued on August 23, 21:00 UTC. We choose the Advisory 13 because it is the latest hurricane forecast issued before the evacuation decision deadline, August 24, 00:00 UTC. To generate SLOSH output, we need to know three parameters, hurricane intensity, landfall direction and forward speed-tide level. The Advisory 13 indicates the landfall direction as northwest, forward speed as 2 knots (2.3 mph), and the intensity at landfall as a tropical storm, which is a weaker than Category 1 storm. To utilize the SLOSH surge output, we first choose the surge output generated with these attributes: Category 0, northwest, and 5 knots-high tide. However, when we check the output, the surge caused by this hurricane profile was negligible and there was no location flooded by surge. In order to understand the impact of surge on evacuation planning, we adjust the storm intensity to Category 3, keep the other profiles the same, and create the flood maps with SLOSH. One of the assumptions in combining the SLOSH and NWM output is that the surge and streamflow work independently on the water height. The main driver for forecasting streamflow with NWM is the precipitation and the surge does not have any impact on streamflow forecast with NWM. There still remains a possibility of a location flooding due to combined water height from surge and streamflow, but in this experiment, we ignore such possibility.

We experiment the model with creating 20 hurricane scenarios with both SLOSH and NWM and compare its result with the 20 scenarios generated with only NWM or SLOSH model. Also, we explore the model by assigning different probability profiles to the hurricane scenarios. First, we assume that each scenario has an equal probability, and in the next setting, we assign linearly increasing probability scenarios. Lastly, we use an exponential function to describe the scenario weight. The most recent forecast has the most weight and the dated one the least. Also, we test the model with different flood threshold levels (0, 1, 2, 3 ft) and study the impact of flood threshold levels on evacuation planning.

4.2 Results

Table 1. Experiment Result

Probability Profile	Calculation Result	NWM				NWM/SLOSH			
		Threshold level (ft)				Threshold Level (ft)			
		0	1	2	3	0	1	2	3
Uniform Weight	# of Staging Areas	2	1	1	1	2	2	2	2
	# of Ambulances, AmBuses	[16,413]	[16,249]	[14,115]	[6,49]	[16,824]	[16,660]	[16,396]	[16,163]
	Avg. # of Evacuating Hospitals	4.3	3.0	2.5	2.2	12.2	11.6	8.4	8.2
	Avg. Demand (Critical)	25.7	17.1	14.5	12.6	57.4	52.7	39.9	38.6
	Avg. Demand (Non-Critical)	223.0	153.3	130.1	112.2	599.6	563.5	412.9	400.2
Linear Weight	# of Staging Areas	2	1	1	1	2	2	2	2
	# of Ambulances, AmBuses	[16,413]	[16,249]	[14,115]	[6,49]	[16,824]	[16,660]	[16,396]	[16,163]
	Avg. # of Evacuating Hospitals	4.8	3.4	2.7	2.2	12.8	11.8	8.6	8.2
	Avg. Demand (Critical)	29.3	19.3	15.5	12.9	61.0	53.8	40.6	38.9
	Avg. Demand (Non-Critical)	253.8	174.4	140.3	115.5	629.3	574.7	420.6	403.5
Expo. Weight	# of Staging Areas	2	1	1	1	2	2	2	2
	# of Ambulances, AmBuses	[16,413]	[16,249]	[14,115]	[6,49]	[16,824]	[16,660]	[16,389]	[16,163]
	Avg. # of Evacuating Hospitals	3.8	2.5	2.1	2.0	11.8	11.1	8.1	8.0
	Avg. Demand (Critical)	24.1	14.8	12.3	12.1	56.1	50.6	38.2	38.1
	Avg. Demand (Non-Critical)	202.2	130.7	108.1	106.8	581.0	542.6	395.3	394.8

As described in the previous section, we ran the model several times with hurricane scenarios obtained from different attributes, and the result is summarized in Table 1. As expected, the hurricane scenarios generated with both SLOSH and NWM incur larger demands (in the form of patients) and require more resources to coordinate the patient evacuation missions. The difference in the average number of evacuating hospitals is approximately 7. To resolve the routing issues from the increased number of evacuating hospitals, the model opens another staging area location. As the threshold level increases, fewer number of hospitals are subjected to evacuation. The scenario probability profiles does not provide a significant difference in the result. Although it is not shown in the table, when we used the exponential weight, the number of vehicles and their staging locations were different from using the other probability profiles. The average demands of both critical and non-critical patients are greatest with scenarios with linear weight. From this, we could infer that the forecast scenarios produced in later period predicted heavier flooding. In this experiment, we assume that no multi-trip is possible. Therefore, the number of vehicles needed for evacuation should decrease in real life since the EMS vehicles may travel more than once between evacuating and receiving hospitals.

5. Conclusion and Future Work

In this paper, we enhance the hurricane scenario generation scheme from our previous work by integrating two origins of flooding, freshwater in inland and storm surge in coastal region, with the state-of-art hydrology models, SLOSH and NWM, and bring the scenarios as our input to the two-stage stochastic optimization model. The solution of the patient evacuation model is closely influenced by the flood threshold level, method of scenario generation, and the scenario probability profiles. The outcome of the model provides a guideline and insight to the decision makers of the patient evacuation operation. With the various hurricane scenarios generated by the forecasting models, the solution advises the decision makers in determining the location of the staging areas. Further, the model indicates which evacuating hospitals are more prone to flooding and which receiving hospitals are more likely to admit patients during a hurricane. The decision makers and hospital representatives could reinforce their facilities and secure more resources such as patient beds to prepare for future hurricanes. We further plan to extend our work in hurricane scenario generation. In general, one can assume that newer forecasts are relatively more accurate than older ones. Therefore, instead of combining the time scries forecasts generated in different periods, we would generate hurricane scenarios at a certain period by perturbing the precipitation, which is the most critical attribute in streamflow prediction. In addition, we would develop a better method to combine the impact of storm surge and streamflow on flood mapping.

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