A Stochastic Lookahead Approach for Disaster Relief Logistics Operations

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Motivation. Many societies in the U.S. are vulnerable to disasters such as earthquakes, hurricanes, floods, wildfires, and terrorist attacks. Hurricanes, in particular, are studied extensively because they affect large areas and populations, and they are relatively easier to predict compared to other disasters. For instance, in 2005, Hurricane Katrina destroyed more than 200,000 houses and cost over $100 billion (Deryugina, Kawano, and Levitt 2018). In recent years, researchers have shown an increased interest in improving the efficiency of disaster relief logistics. In the aftermath of a hurricane landfall, there are usually shortages in water, food, and medicine - critical resources for survival. Under this situation, disaster relief logistics informs operational decision making under uncertainty, which involves mobilizing various resources to help the affected population by a disaster in a timely fashion. The importance of the relief logistics operations planning is indisputable.

Problem Statement. The most challenging problem in humanitarian logistics is the coordination of logistical arrangements (Kovács and Spens 2009). To analyze the disaster relief logistics, Apte (2009) separates the operations during the disaster life cycle into four phases: mitigation, preparedness, response, and recovery. In this paper, we focus on disaster relief operations planning to deliver relief items to the affected area during the response phase. Vanajakumari, Kumar, and Gupta (2016) stated that most emergency administrators prefer a flexible and realistic optimization model for this problem. In order to have a realistic model, we consider the transportation cost as well as social cost (in terms of the deprivation cost) in the objective of our model. Pérez-Rodríguez and Holguín-Veras (2015) pointed out the importance of not ignoring the social cost incurred by the affected population which could be significantly reduced by using an appropriate relief item distribution strategy. Also, by considering the uncertainty parameters caused by the evolving information during the response phase, our model meets the requirements for flexibility and reality. Specifically, assume that we have a timeline for the response phase starting from $day\,0$ (one day before the landfall), and ending on $day\,T$ (the last day of the response phase). On $day\,0$, the demand, supply, and road network conditions for remaining days are unclear and we only have access to a stochastic forecast of the track and intensity of the hurricane. After landfall, for

day 1 to *day* $(T-1)$, the uncertainty regarding the stochastic forecast keeps evolving based on the observational data and historical data.

Solution Approach. As Santoso et al. (2005) and Vahdani et al. (2018) have done in the literature, various uncertain factors involved in disaster relief operations planning are typically incorporated into the logistics planning optimization problem using a two-stage stochastic programming (2SSP) model. In this paper, we introduce a static 2SSP model to solve the disaster relief logistics planning problem when the underlying random variables are assumed to follow a given static probability distribution. The static 2SSP model aims to minimize the total cost of the relief logistics operations, including the transportation cost for the relief items and the deprivation cost of the unsatisfied demand. The decision variables in the static 2SSP model are separated into state variables and local control variables. The state variables define the network system states from *day* 0 to *day* T, which are treated as first-stage decision variables in the static 2SSP model; the second-stage decision variables are the local control variables for the specific transportation plans under each scenario. The state and local control decision variables mentioned before describe the logistics operations plan for each day, such as the amount of the flow of transported supplies between different nodes in the supply chain network, the inventory level of relief items at each node, the satisfaction status of the daily demand, the number of days since the last time that the demand was fully satisfied, and the delivery status of each distribution node for each day. The constraints in the models are briefly summarized as follows: (a) The inventory capacity constraints for different types of nodes in the network, as well as the supply limit constraints; (b) The demand for relief items on each day can be fulfilled by the existing inventory and new deliveries; (c) If a point of distribution receives delivery of relief items on a particular day, the amount of delivery must be large enough to cover the demand; (d) Any remaining inventory level will drop down to 0 if it is not sufficient to satisfy the demand on each day; (e) The number of unsatisfied days associated with a point of distribution keeps increments by 1 each day the demand is not satisfied.

One potential drawback of a static 2SSP model is that it fails to address the dynamic evolution of the aforementioned uncertain factors in the problem. To this end, we propose a stochastic lookahead framework that implements 2SSP in a rolling-horizon fashion, which is commonly used to model sequential dynamic decision making under evolving uncertainty (Hasani and Mokhtari 2018). Specifically, as shown in Fig. 1, the rolling horizon approach separates the timeline into sub-problems for each day (SP_t). For each sub-problem before *day* T, we run the general 2SSP model at the beginning of each day. On *day* T, a deterministic optimization model is performed. We refer to the process of constructing and solving a model for each day under the proposed framework as the rolling 2SSP. The key idea of the stochastic lookahead framework is that we solve a 2SSP model on the current day. Only the logistics plans for the current day are implemented, and subsequently

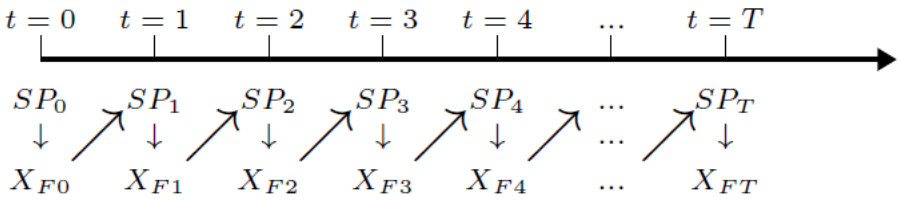


Figure 1 **Illustration of Rolling Horizon Timeline**

the horizon is shifted. At the beginning of the next day, the state of the systems is measured or estimated by the observed data on the next day, and a new optimization problem is solved using this new information. Therefore, the actual disaster relief logistics operations during the days on the timeline is $\{X_{F0}, X_{F1}, X_{F2}...\}$.

Results. To evaluate the performance of the proposed stochastic lookahead framework, we compare it with the static 2SSP model. Here, the static 2SSP model contains a set of scenarios for the second-stage, where the total number of scenarios equal to the total number of the sample paths in the proposed lookahead framework. We evaluate the performance of each approach by their respective expected costs (including transportation and social costs) via a out-of-sample test using a set of sample paths. The network instance in our numerical experiments is inspired by the network of New Orleans City used by Pérez-Rodríguez and Holguín-Veras (2015). We use Gurobi 7.0.2 to solve all the optimization models with the default setting.

Table 1 **Numerical Result**

	243 Sample Paths		100000 Sample Paths	
	Static 2SSP	Rolling 2SSP	Static 2SSP	Rolling 2SSP
Transportation Cost ($)	154089	173126	156963	172644
Deprivation Cost ($)	68105	37758	78042	40280
Total Cost ($)	222195	210884	235005	212924
Computational Time (min)	360	31.35	360	137.11
Optimality Gap	32.3%	-	42.5%	-

We compared the performances of the two approaches on two instances in our preliminary numerical experiments: a smaller instance with five periods and three scenarios per period, totaling 243 sample paths, and a larger instance with five periods and ten scenarios per period, totalling 100000 sample paths. For the smaller instance, we randomly sample 50 scenarios for the static 2SSP, and 3 sample paths for each roll of the rolling 2SSP, and test the performances of their respective solutions via an out-of-sample test with all 243 sample paths. For the larger instance, we randomly sample 100 scenarios for the static 2SSP, and 10 sample paths for each roll of the rolling 2SSP, and test their performances via an out-of-sample test with an independently sampled 500 sample paths.

Our preliminary numerical results are summarized in Table 1. Here, the computational time for rolling 2SSP is calculated as the average computational time for each sample path. We see that compared with the static 2SSP, the rolling 2SSP can provide solutions that correspond to a lower overall expected cost (5.09% and 9.39% lower in the smaller and larger instances, respectively) than the ones given by the static 2SSP. We can see that most of the cost savings come from the deprivation cost, indicating that the decision flexibility offered by the rolling 2SSP is beneficial, since it allows the key logistics decisions to be adaptive to the sample path information. We are in the process of developing scenario decomposition algorithms to enhance the computational efficiency for solving both static and rolling 2SSPs.

Conclusions. In disaster relief logistics planning for relatively predictable disasters such as hurricanes, decision makers prefer a flexible and realistic operational plan to minimize the total expected cost, including transportation and social costs. Based on our preliminary numerical experiments, we observe that the proposed stochastic lookahead framework, which integrates two-stage stochastic programming with the rolling-horizon procedure, is able to achieve a more cost-effective logistics operation plan than the one provided by a static two-stage stochastic program.

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