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# Integrated Hurricane Relief Logistics and Evacuation Planning under Forecast Uncertainty: A Case Study for Hurricane Florence

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## Abstract

In this paper, we study an integrated hurricane relief logistics and evacuation planning (HRLEP) problem. We propose stochastic optimization models and methods that integrate the hurricane relief item pre-positioning problem and the hurricane evacuation planning problem, which are often treated as separate problems in the literature, by incorporating the forecast information as well as the forecast errors (FE). Specifically, we fit historical FE data into an auto-regressive model of order one (AR-1), from which we generate FE realizations to create evacuation demand scenarios. We compare a static decision policy based on the proposed stochastic optimization model with a dynamic policy obtained by applying this model in a rolling-horizon (RH) procedure. We conduct a preliminary numerical experiment based on real-world data to validate the value of stochastic optimization and the value of the dynamic policy based on the RH procedure.

## Keywords
Hurricane evacuation and relief logistics, stochastic programming, rolling horizon, auto-regressive model

## 1. Introduction

Hurricanes are among the deadliest disasters in the US. Hurricane Katrina in 2005 alone caused about 1800 deaths and an estimated 108 billion US dollars worth of infrastructure damage [1]. Population under the threat of a hurricane evacuates to safe shelters because of personal safety concerns, power outages, and flooding [2]. While most evacuees shelter in hotels or resort to families and friends, around 11% evacuees from the potential affected areas, which we refer to as demand points (DPs), are evacuated to the shelter points (SPs) [2]. In the meantime, relief items (such as food, water, and medical kits) are shipped from distribution centers (DCs) to the SPs. Clearly, the operations of evacuation and the relief item pre-positioning at the SPs must be coordinated to ensure the well-being of the evacuees at the shelters. In this paper, we study an integrated hurricane relief logistics and evacuation planning (HRLEP) problem.

Evacuation is a multi-period operation, which typically starts approximately two to three days before the hurricane's predicted landfall time, depending on the hurricane's severity [3]. A timely evacuation plan is crucial to ensure sufficient time for the evacuation operation. Every six hours after the hurricane's formation, the National Hurricane Center (NHC) issues a forecast of the hurricane attributes up to the next five days including the hurricane's projected track (longitude, latitude) and intensity (wind speed). The projected landfall location of an impending hurricane determines the risk zone. Inside the risk zone, the evacuation demand from the DPs, i.e., the number of evacuees, depends on the affected population's behaviors and the hurricane's attributes [4], which we assume to be characterized by the hurricane's intensity and location. In the case of a deterministic hurricane forecast, one may perform a deterministic demand estimation and create a deterministic optimization model for the HRLEP problem. However, the hurricane forecast is imperfect and subject to FEs, which imposes uncertainty on the hurricane's future attributes and hence the demand realization. A deterministic optimization model may be insufficient to address the challenges brought by the various sources of uncertainty in the hurricane event, and one typically resort to tools and models in optimization under uncertainty, such as stochastic optimization.

Given a stochastic process that characterizes the uncertain hurricane attributes over time with a known probability distribution, a fully adaptive multi-stage stochastic programming (MSSP) model can be used to create dynamic decision policies. However, MSSP models are complex and computationally expensive to solve [5]. Two-stage stochastic programming (2SSP) models are more desirable in this situation as they are computationally less demanding. Despite its efficiency, 2SSP models only produce static decisions that may suffer from lack of adaptability. This issue may be partially addressed by the so-called rolling horizon (RH) approach [6]. There is an extensive set of literature on hurricane evacuation and relief logistics operation, which are typically treated as two separate problems. For example, the pre-positioning of emergency relief items in a logistics network has been studied both in a single-period setting and in a dynamic multi-period setting with uncertainty in the supply and demand of relief items [7, 8]. For evacuation, a dynamic forecast-driven Markov decision process model has been used to determine the evacuation timing decisions [9]. The integrated problem of evacuation and relief logistics planning has not appeared in the literature until recently, where the problem is studied in a single-period setting [10]. There is a lack of research that incorporates evacuation into disaster relief logistics planning in an integrated network under a multi-stage setting.

In this paper, we aim to address this issue by studying both a static policy given by a 2SSP model and a dynamic policy by using the 2SSP model in the RH procedure for multi-stage integrated evacuation and disaster relief logistics planning. In this procedure, we sequentially solve a stochastic look-ahead model (SLAM) at every period, which corresponds to a 2SSP model defined for the remaining of the planning horizon, and only implements the decisions that apply to the current period. The remainder of the paper is structured as follows: Section 2 describes the mathematical formulation of HRLEP problem as a 2SSP model. Section 3 presents the experimental setup, a case study, and the corresponding results. Section 4 summarizes the paper with some concluding remarks.

## 2. Problem formulation

This section discusses the model formulation for the proposed 2SSP model for the HRLEP problem. We consider a planning horizon of $T$ periods : $\mathcal{T} = \{1,...,T\}$. At any time period $t' \in \mathcal{T}$, we define a SLAM at $t'$ for the remaining planning horizon of $\mathcal{T}' = \{t', t'+1, ..., T\}$. Let $I, J, K$ represent the sets of DPs, SPs, and DCs, respectively, and let $S$ represent the set of hurricane scenarios for 2SSP model. For simplicity, we make the following assumptions in our model: (i) The DCs and SPs can be opened at any time $t \in \mathcal{T}$, which is available for use immediately, and once opened, they will stay open until the end of the planning horizon; (ii) The evacuees evacuated to an SP cannot be moved to other SPs; (iii) We treat the relief items as a single-commodity package that contains all essential items needed by an evacuee. The problem parameters are defined as follows:

| | |
|---|---|
| $D_i^{POP}$ | The total population (maximum potential demand for evacuation) of DP $i \in I$ |
| $q_j/q_k$ | Capacity for the number of evacuees/relief items at SP $j \in J$ / DC $k \in K$ |
| $c_j^F/c_k^F$ | One-time fixed setup cost of SP $j \in J$ / DC $k \in K$ upon activation |
| $c_k^P$ | Unit procurement cost of relief items at DC $k \in K$ |
| $c_{ij}^E$ | Unit evacuation cost from DP $i \in I$ to SP $j \in J$ |
| $c_{kj}^R/c_{j'j}^R$ | Unit transportation cost of relief items from DC $k \in K$ or SP $j' \in J$ to SP $j \in J$ |
| $c^{PE}$ | Unit penalty cost for not evacuating a person needing evacuation at a period |
| $c_j^G/c_j^H$ | Unit cost for *emergency/unused* relief items shipped to/from SP $j \in J$ |
| $c_j^{InvR}/c_k^{InvR}$ | Unit inventory cost of relief items in SP $j \in J$ / DC $k \in K$ per period |
| $c_j^{InvE}$ | Unit operating cost of SP $j \in J$ (per evacuee) per period |
| $p_s$ | Probability of occurrence for scenario s $\in$ S |

At each period $t'$, the hurricane's attributes in the remaining planning horizon, $t'+1, ..., T$ are uncertain. To come up with a 2SSP model, we represent the uncertain demand at periods $t \in \{t'+1, ..., T\}$ in the form of scenarios. Each scenario $s \in S$ is a sample path that represents the evolution of a hurricane's attributes from $t'+1$ until $T$ and corresponding demand realization vector $\{[D_{is}^{t'+1}]_{i\in I}, ..., [D_{is}^{T}]_{i\in I}\}$, which represents the fraction of the remaining population at $i \in I$ to evacuate each time $t$. For simplicity, the demand realization is computed via a deterministic mapping from the realization of the hurricane's attributes (see Section 3.1 for details). This captures the empirical behavior analysis results for hurricane evacuation [4].

The first-stage decisions are defined as follows:

| | |
|---|---|
| $z_j^t/z_k^t$ | Whether or not $j \in J/k \in K$ is open during time period $t \in \mathcal{T}'$ |
| $\ell_j^t/\ell_k^t$ | Inventory level of relief items at $j \in J/k \in K$ at the end of period $t \in \mathcal{T}'$ |
| $y_{ij}^{t'}$ | Number of people to evacuate from $i \in I$ to $j \in J$ at time $t'$ |
| $u_i^{t'}$ | Number of people whose evacuation need/demand is not met at $i \in I$ at time $t'$ |
| $e_i^{t'}/e_j^{t'}$ | Number of evacuees at $i \in I/j \in J$ at the end of period $t'$ |
| $x_k^{t'}$ | Amount of relief items procured at $k \in K$ in time period $t'$ |
| $x_{kj}^{t'}/x_{j'j}^{t'}$ | Amount of relief items shipped from $k \in K/j' \in J \setminus \{j\}$ to SP $j \in J$ at time $t'$ |

$g_j^{t'}/h_j^{t'}$ Amount of *emergency*/*unused* relief items shipped to/from $j \in J$ in time $t'$

The first-stage decisions can be categorized by *local* variables and *state* variables. Specifically, $z_j^t$, $z_k^t$, $\ell_j^t$, and $\ell_k^t$ are the state variables that characterize the state of the logistics system over time. All other first-stage variables are local variables for period $t'$ only.

The second-stage decision variables are scenario-dependent, which are defined as follows:

- $y_{ijs}^t$ Number of people to evacuate from $i \in I$ to $j \in J$ at time $t \in \mathcal{T}' \setminus \{t'\}$ in $s \in S$
- $u_{is}^t$ Number of people whose evacuation need/demand is not met at $i \in I$ at time $t \in \mathcal{T}' \setminus \{t'\}$ in $s \in S$
- $e_{is}^t/e_{js}^t$ Number of evacuees at $i \in I / j \in J$ at the end of period $t \in \mathcal{T}'$ in $s \in S$
- $x_{ks}^t$ Amount of relief items procured at $k \in K$ in time period $t \in \mathcal{T}' \setminus \{t'\}$ in scenario $s \in S$
- $x_{kjs}^t/x_{j'js}^t$ Number of relief items shipped from $k \in K / j' \in J \setminus \{j\}$ to $j \in J$ at time $t \in \mathcal{T}' \setminus \{t'\}$ in $s \in S$
- $g_{js}^t/h_{js}^t$ Amount of *emergency*/*unused* relief items shipped to/from $j \in J$ in time $t \in \mathcal{T}' \setminus \{t'\}$ in scenario $s \in S$

At time $t'$, the values of the state variables from $t'-1$, i.e., $\hat{\ell}^{t'-1}$ and $\hat{z}^{t'-1}$, become input parameters to the SLAM. At $t'=1$, we assume the initial conditions are $\ell_j^0, z_j^0, e_j^0 = 0,\ \forall j \in J$, $\ell_k^0, z_k^0 = 0,\ \forall k \in K$, and $e_i^0 = D_i^{POP},\ \forall i \in I$. The SLAM at $t'$ is a 2SSP model that combines the first-and second-stage models defined as follows:

**The first-stage model**

$$\min \sum_{j\in J} c_j^F\left(z_j^T - \hat{z}_j^{t'-1}\right) + \sum_{k\in K} c_k^F\left(z_k^T - \hat{z}_k^{t'-1}\right) + \sum_{k\in K} c_k^P x_k^{t'} + \sum_{j\in J}\sum_{j'\in J} c_{jj'}^R x_{jj'}^{t'} + \sum_{j\in J}\sum_{k\in K} c_{kj}^R x_{kj}^{t'} + \sum_{i\in I}\sum_{j\in J} c_{ij}^E y_{ij}^{t'} + \sum_{j\in J} c_j^{invE} e_j^{t'} + \sum_{t\in\mathcal{T}'}\sum_{j\in J} c_j^{InvR}\ell_j^t + \sum_{t\in\mathcal{T}'}\sum_{k\in K} c_k^{InvR}\ell_k^t + \sum_{j\in J} c_j^G g_j^{t'} + \sum_{j\in J} c_j^H h_j^{t'} + \sum_{i\in I} c_{t'}^{PE} u_i^{t'} \tag{1a}$$

$$\text{s.t. } \hat{z}_k^{t'-1} \le z_k^{t'},\ \forall k \in K;\ z_k^{t-1} \le z_k^t,\ \forall k \in K, \forall t \in \mathcal{T}' \setminus \{t'\} \tag{1b}$$

$$\hat{z}_j^{t'-1} \le z_j^{t'},\ \forall j \in J;\ z_j^{t-1} \le z_j^t,\ \forall j \in J, \forall t \in \mathcal{T}' \setminus \{t'\} \tag{1c}$$

$$\ell_k^t \le q_k z_k^t,\ \forall k \in K, \forall t \in \mathcal{T}' \tag{1d}$$

$$\ell_j^t \le q_j z_j^t,\ \forall j \in J, \forall t \in \mathcal{T}' \tag{1e}$$

$$\sum_{j\in J} y_{ij}^{t'} + u_i^{t'} = D_i^{t'} \hat{e}_i^{t'-1},\ \forall i \in I \tag{1f}$$

$$e_i^{t'} = \hat{e}_i^{t'-1} - \sum_{j\in J} y_{ij}^{t'},\ \forall i \in I \tag{1g}$$

$$\sum_{i\in I} y_{ij}^{t'} + \hat{e}_j^{t'-1} = e_j^{t'},\ \forall j \in J \tag{1h}$$

$$e_j^{t'} \le q_j z_j^{t'},\ \forall j \in J \tag{1i}$$

$$\hat{\ell}_j^{t'-1} + \sum_{k\in K} x_{kj}^{t'} + \sum_{j'\in J, j\neq j'} x_{j'j}^{t'} - \sum_{j'\in J, j\neq j'} x_{jj'}^{t'} - e_j^{t'} + g_j^{t'} - h_j^{t'} = \ell_j^{t'},\ \forall j \in J \tag{1j}$$

$$\sum_{j'\in J, j\neq j'} x_{jj'}^{t'} \le \hat{\ell}_j^{t'-1} + g_j^{t'} - e_j^{t'},\ \forall j \in J \tag{1k}$$

$$\hat{\ell}_j^{t'-1} + g_j^{t'} - e_j^{t'} \le q_j z_j^{t'},\ \forall j \in J \tag{1l}$$

$$\sum_{j\in J} x_{kj}^{t'} \le \hat{\ell}_k^{t'-1},\ \forall k \in K \tag{1m}$$

$$\ell_k^{t'} = \hat{\ell}_k^{t'-1} - \sum_{j\in J} x_{kj}^{t'} + x_k^{t'},\ \forall k \in K \tag{1n}$$

$$z_j^t \in \{0,1\},\ \forall j \in J,\ \forall t \in \mathcal{T}'; z_k^t \in \{0,1\}, \forall k \in K, \forall t \in \mathcal{T}' \tag{1o}$$

$$\ell_k^t \ge 0,\ \forall k \in K,\ \forall t \in \mathcal{T}'; \ell_j^t \ge 0,\ \forall j \in J,\ \forall t \in \mathcal{T}'; u_i^{t'}, e_i^{t'} \ge 0,\ \forall i \in I; e_j^{t'}, h_j^{t'}, g_j^{t'} \ge 0,\ \forall j \in J; x_k^{t'} \ge 0,\ \forall k \in K \tag{1p}$$

$$y_{ij}^{t'} \ge 0,\ \forall i \in I,\ \forall j \in J; x_{kj}^{t'} \ge 0,\ \forall k \in K, \forall j \in J; x_{jj'}^{t'} \ge 0,\ \forall j, j' \in J : j \neq j' \tag{1q}$$

**The second-stage model**

$$\min \sum_{s\in S} p_s \sum_{t\in\{t'+1,\dots,T\}} \left( \sum_{i\in I}\sum_{j\in J} c_{ij}^E y_{ijs}^t + \sum_{j\in J} c_j^{invE} e_{js}^t + \sum_{k\in K} c_k^P x_{ks}^t + \sum_{j\in J}\sum_{j'\in J} c_{jj'}^R x_{jj's}^t + \sum_{j\in J}\sum_{k\in K} c_{kj}^R x_{kjs}^t + \sum_{j\in J} c_j^G g_{js}^t + \sum_{j\in J} c_j^H h_{js}^t + \sum_{i\in I} c_t^{PE} u_{is}^t \right) \tag{2a}$$

$$\text{s.t. } e_{is}^{t'} = e_i^{t'},\ \forall i \in I, \forall s \in S \tag{2b}$$

$$e_{js}^{t'} = e_j^{t'},\ \forall j \in J, \forall s \in S \tag{2c}$$

Constraints similar to (1f) $-$ (1n), $\forall t \in \{t'+1,...,T\}$, $\forall s \in S$ with the first-stage variables replaced by their second-stage copies

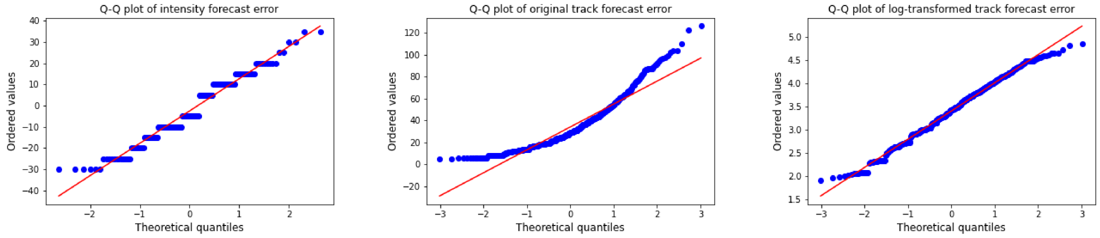
The first two terms of the first-stage objective (1a) represent the fixed cost of opening SPs and DCs, respectively. The third term represents the total cost of procuring relief items at DCs. The fourth and fifth terms represent the cost of transporting relief items among SPs and from DCs to SPs. The last two terms represent the inventory holding costs of relief items at DCs and SPs. Constraints (1b) and (1c) ensure that the DCs and SPs stay open until the end of periods once they are decided to be open. Equations (1d), (1l), and (1m) are the inventory and supply capacity constraints of the DCs. Similarly, constraints (1e) and (1k) represent SPs' inventory and supply capacities. Constraints (1n) and (1j) are the balance constraints for the supply and inventory of relief items at DCs and SPs, respectively. Constraint (1f) ensures demand satisfaction, while constraint (1g) represents the number of evacuees at DPs. Constraint (1h) represents the number of evacuees at SPs, and constraint (1i) is the capacity constraint for the number of evacuees at SPs. Objective (2a) is the expected value of second-stage cost from period $t'+1$ until the hurricane's landfall at $T$. We use the standard Benders decomposition method to solve 2SSP models by treating the first-stage and the second-stage models as the master and subproblems, respectively.

### 2.1 The rolling horizon approach

A 2SSP model at $t = 1$ can only provide a static decision policy. In this model, the logistics and evacuation decisions $\forall t \in \mathcal{T}$ are made at $t = 1$ that depend on the point forecast at $t = 1$ and the hurricane attributes' possible future realizations. Since a hurricane's attributes and forecasts change over time, a static model fails to adapt to the dynamic evolution of the hurricane's information. The rolling horizon approach naturally generates a dynamic policy in an online fashion where a SLAM is solved at every period, but only the decisions that apply to the current period are implemented. At every period $t' \in \mathcal{T}'$, the SLAM at $t'$ utilizes the actual realization at $t'$ and the most updated forecast available. Let $X_{t'}$ and $Y_{t'}$ be the state and local variables of SLAM at $t'$, and after we solve the SLAM at $t'$, we implement an optimal solution $\hat{X}_{t'}$ and $\hat{Y}_{t'}$ and compute the immediate cost $Z^*_{t'}(\hat{X}_{t'}, \hat{Y}_{t'})$ for the current stage $t'$. The values of the state variables $\hat{X}_{t'}$ are used as input parameters for the SLAM at $t'+1$ as we roll forward to the next stage. After solving SLAM for all $t' \in \mathcal{T}$ over a sample path, we compute the cumulative cost of the rolling-horizon policy on this sample path, $Z^*_{RH} = \sum_{t' \in \mathcal{T}} Z^*_{t'}(\hat{X}_{t'}, \hat{Y}_{t'})$.

## 3. Experimental setup and results

In this section, we discuss our experiment setup and some preliminary computational results. We start by discussing how we model the forecast uncertainty. Our stochastic model for the forecast error (FE) is constructed based on data available from the NHC's forecast verification report [11], which is released each year at the end of every hurricane season, including both the track FE and the intensity FE. Our preliminary calculation indicates that the Pearson correlation coefficient of FE between two subsequent periods is greater than 0.7, which motivates us to model the track and intensity FE data using auto-regressive models of order 1 (AR-1). Let $\xi^t$ represent the FE at period $t$, then according to the AR-1 model: $\xi^t = \rho \xi^{t-1} + \varepsilon^t$, where $\varepsilon^t \overset{\text{iid}}{\sim} N(0, \sigma^2)$, $\forall t \in \mathcal{T} \setminus \{1\}$ and $\xi^1$ is deterministic. To validate the model assumption, we provide the Q-Q plots of historical intensity and track FE at 24 hours prior to landfall in Figures 1a and 1b. The Q-Q plot supports the normality assumption of intensity FE. In contrast, the non-normal distribution of the track FE is due to heavy tails observed. To address this, we transform the track FE data using a log transformation, and we see that the normality assumption is supported by the Q-Q plot in Figure 1c for the transformed data.




(a) Intensity forecast error (b) Original track forecast error (c) Transformed track forecast error

Figure 1: Q-Q plot of historical hurricane forecast errors at 24 hours prior to the hurricane's landfall

We estimate parameters $(\rho, \sigma)$ in the AR-1 model using maximum likelihood estimation (MLE), as $(\rho_{mle}, \sigma_{mle})$ based on the NHC's official FE data of the storms from 2017 to 2021 [11]. For a given realization of $\xi^{t-1}, \rho_{mle}$, and $\sigma^2_{mle}$, a realization of $\xi^t$ can be obtained by sampling $\varepsilon^t \sim N(0,\sigma^2_{mle})$. We thus randomly sample a number of realizations of $\varepsilon^t, \forall t \in \mathcal{T}$ to create an $\varepsilon$-grid for track and intensity errors. To generate a scenario (sample path), for each $t = 1,2,\ldots,T$, we randomly pick a realization of $\varepsilon^t$ from the $t^{th}$ column vector of $\varepsilon$-grid to compute $\xi^t$.

### 3.1 Case study

Our case study focuses on Hurricane Florence 2018 in South Carolina (SC), assuming the coastal line to be straight for simplicity. We define the study region as a 200-miles area around the endpoints of the coastal line, encompassing eight coastal SC counties with high hurricane vulnerability as the Demand Points (DPs). We represent the DPs' locations by projecting the respective counties' central latitudes (lats) and longitudes (longs) onto the coastal line. The SC Emergency Management Division (SCEMD) divides the state of SC into four hurricane regions. We select 11 hurricane sub-regions with high vulnerability in the north, central, and south regions as our candidate SPs, with their central locations and aggregated shelter capacities. Additionally, we choose 12 counties in the western hurricane region with their central locations (lats, longs) as our DCs.

We consider a planning horizon of 10 periods, each being 12 hours long, starting at 0-hour ($t_1$) to 120-hour ($t_{11}$). At $t_1$, the hurricane's track and intensity forecast from $t_2$ until $t_{11}$ is given by NHC's official (point) forecast. We assume that the hurricane makes landfall deterministically at $t_{11}$. The track FE at every scenario represents the deviation between the realized hurricane's position and the point forecast, along the axis of the coastal line. Figure 2 presents the locations and a set of sample hurricane tracks. We set $D^{POP}_i$, $\forall i \in I$ to be 5% of the vulnerable population of the respective DPs [2].

We assume that the demand at each DP at any period is a function of the hurricane's location and intensity. To represent the hurricane's track locations, we define the $x$- and $y$- axes by the coastal line (which is assumed to be a straight line) and its normal. A positive demand for DP $i \in I$ at a period $t \in \mathcal{T}$ will incur if its location is within certain threshold values in both the $x$- and $y$- axes, $(x_{max}, y_{max})$, from the hurricane's location, i.e., $D^t_{is} = \min\left\{\frac{int^t_s}{int_{\max}}, 1\right\} \times \max\{1 - \frac{dx^{t,s}_i}{x_{max}}, 0\} \times \max\{1 - \frac{dy^{t,s}_i}{y_{max}}, 0\}$ where $int_{\max}$ is the maximum intensity of a hurricane considered, $int^t_s$ is the hurricane's intensity at period $t$ on sample path $s$, and $dx^{t,s}_i$ and $dy^{t,s}_i$ are the distances between DP $i$ and the hurricane's location at period $t$ on sample path $s$, respectively.

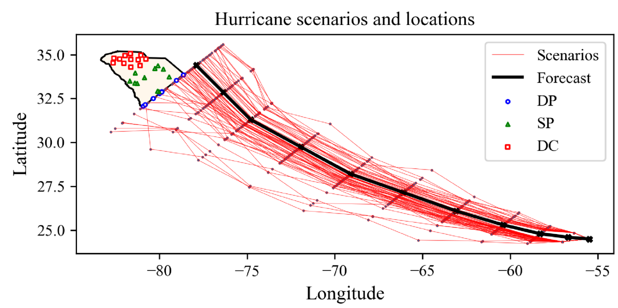
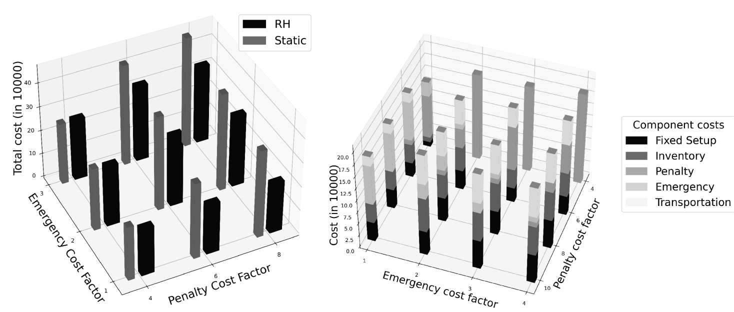



Figure 2: Location of DPs, SPs, DCs and hurricane scenarios

### 3.2 Out-of-sample evaluation

The out-of-sample (OOS) evaluation for the RH policy is straightforward. To conduct an OOS evaluation on the static 2SSP policy for sample path $s^o$, we first solve the 2SSP model at $t = 1$. Then for each period $t \in \{2,\ldots,T\}$, we pick the recourse solution of scenario $s$ closest to $s^o$ among all scenarios used in the 2SSP model at $t = 1$ in terms of the DP demand vector. Using the number of evacuees $\hat{y}^t_{ijs}$ as an upper bound for the number of evacuees on arc $(i,j)$, we solve a deterministic optimization problem to get the values of other local variables.




(a) OOS evaluation (b) Sensitivity analysis of the 2SSP model

Figure 3: OOS evaluation and sensitivity analysis on various cost factors.

### 3.3 Results

We now present numerical results from our preliminary experiments. Firstly, we pick $S = 50$ to be the number of scenarios to use through an in-sample stability test. Furthermore, Figure 3a presents the average OOS cost over 50 replications of both the RH and static policy for different cost factors, $G_{fact}$ and $P_{fact}$. The RH model exhibits an average total cost that is 13% lower than the static policy, highlighting the benefits of adaptive decision making. In contrast, the static 2SSP model is limited in its ability to evacuate beyond a certain number of evacuees as it must satisfy demand on a sample path with the static solution obtained without the sample-path information. As $c^{PE}$ increases, the static policy results in higher penalty costs and fewer evacuations. Moreover, the rate of change of the cost difference for RH and static 2SSP is less for the rate of change of $c^G$ than $c^{PE}$. This indicates that the cost of the static 2SSP model on the evacuation side is more significant than on the relief logistics side. Thus, the static policy, when applied to an OOS, results in higher penalty costs and fewer evacuations. In contrast, RH adapts to demand realizations in an online fashion, leading to lower overall costs.

Figure 3b demonstrates the sensitivity analysis of a 2SSP model for different cost factors $G_{fact}$ and $P_{fact}$, which controls the values of $c^G$ and $c^{PE}$, respectively. Specifically, the penalty cost dominates among all cost components for smaller values of $c^{PE}$. As $c^{PE}$ increases, the total penalty cost decreases, and evacuation and relief supplies play a more significant role in fulfilling demand. It is important to note that emergency costs only occur after the SPs are activated to provide relief items to evacuees. In contrast, penalty costs can be incurred independently of all other costs. Furthermore, emergency costs become significant only for small $c^G$ values but become negligible for higher $c^G$ values, as relief logistics are relatively less expensive in the latter case. Thus, decision-makers can utilize this trade-off analysis to select appropriate values of $c^{PE}$ and $c^G$ based on their impact on the overall cost structure.

## 4. Conclusion

This paper considered the use of dynamically evolving uncertain hurricane attributes in an integrated HRLEP problem. We modeled and solved the integrated HRLEP problem using a *static* 2SSP model and an *online* RH approach. We fit an AR-1 model using historical FE data, from which we created evacuation demand scenarios for the 2SSP model. We demonstrated the benefit of the RH approach over a static 2SSP model with an out-of-sample test. For future research, we will consider the case where the hurricane's landfall time is random, using a multi-stage SP model.

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