Proceedings of the IISE Annual Conference & Expo 2025
E. Gentry, F. Ju, X. Liu, eds.

A Stochastic Service Network Design Model for Disaster Logistics Planning: A Case Study for the State of South Carolina

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Abstract

In this paper, we present a logistics planning problem focused on prepositioning essential relief commodities in anticipation of a hurricane landfall. This problem can be considered as a service network design problem, and we study its simplified version as a stochastic multi-period network flow model under the framework of two-stage stochastic programming with recourse. In the first stage, the model works to optimize the prepositioning of relief commodities for all periods, and in the second stage, it focuses on demand fulfillment, demand shortage levels, and transportation flows decisions. We assume that the hurricane's evolution over time can be approximated as a Markov chain, where each Markovian state is characterized by the hurricane's attributes (location and intensity). Demand quantities at each point are calculated based on these evolving attributes, allowing for more accurate scenario generation. To solve the model efficiently, we apply Benders decomposition for improved computational performance. Our numerical results and sensitivity analyses based on a case study for the state of South Carolina demonstrate the effectiveness of this scenario-based approach.

Keywords
Stochastic programming, logistics planning, network flow, Benders decomposition

1. Introduction

Hurricanes, tornadoes, and earthquakes are examples of extreme disasters that can leave behind a great deal of destruction and casualties. Numerous areas in the US and other countries are susceptible to these natural disasters. Emergency response after such a disaster may be ineffective if supplies are insufficient or their deployment is delayed. The primary objective of emergency response activities is to provide shelter and essential supplies to the affected area as soon as possible. To achieve this objective, an important aspect of logistics planning involves pre-positioning these items at strategic locations to ensure key relief commodities, such as food, water and medical kits, are accessible when required. In this paper, we focus on hurricane disaster events and study a logistics planning problem in anticipation of a hurricane landfall.

A significant challenge in developing an effective pre-positioning plan lies in the uncertainty surrounding the occurrence of hurricanes, including their potential locations and magnitudes. Hurricane events can typically be identified with confidence a few days prior to their landfall [1]. The National Hurricane Center (NHC) in the United States issues prediction advisories that include details about a hurricane's characteristics, such as its projected path, intensity, and the areas likely to be impacted. These forecasts assist emergency management officials in prepositioning supplies, a practice proven to enhance the effectiveness of emergency relief efforts [2]. Specifically, decision makers determine a study region at the risk of being affected by the hurricane in which there are two sets of demand points, PoDs (points of distribution) and shelters. The relief commodities can be sourced from the warehouses and supply locations and prepositioned at regional staging areas (RSAs) before being distributed to individual demand points. After the hurricane makes landfall, the prepositioned relief commodities can be transported from the warehouses, suppliers and RSAs to PoDs and shelters to meet the demand. However, decision makers must grapple with substantial uncertainties as hurricane's attributes (location and intensity) evolve over time. If these attributes were known beforehand, the problem could be formulated as a deterministic network flow model for hurricane logistics planning. Nevertheless, forecast information is inherently imperfect, introducing uncertainty in demand realization and this uncertainty necessitates the use of optimization techniques under uncertainty, such as stochastic programming.

In this paper, we formulate a two-stage stochastic programming (2SSP) model to address both pre- and post-hurricane logistics planning incorporating uncertainty in demand for relief items. Furthermore, we present experimental results based on a case study conducted in the state of South Carolina, demonstrating the advantages of the 2SSP model over a deterministic version. The remainder of the paper is organized as follows. In Section 2, we describe the problem setting and the mathematical formulation of our logistics network flow problem as a 2SSP model. In Section 3, we present a case study and perform sensitivity analyses. In Section 4, we summarize the paper with concluding remarks.

2. Problem description

In this section, we begin by outlining the logistics network that serves as the foundation for our logistics planning problem definition. Next, we present the assumptions underlying our problem formulation, followed by the introduction of a baseline deterministic optimization model. Finally, we describe the two-stage stochastic programming model for our problem to minimize the total expected penalty cost and logistics cost over the planning horizon.

2.1 Logistics network

We consider a service network design model that is formulated as a multi-period network flow problem. The set of nodes $\mathcal{V} = \mathcal{V}_0 \cup \cdots \cup \mathcal{V}_3$ includes suppliers/warehouses, shelters, RSAs (regional staging areas or transshipment nodes), and PoDs (points of distribution). RSAs are locations where commodities will be prepositioned before being distributed to individual demand points. Additionally, the arc set consists of all links except the links between PoDs and shelters. Demand occurs exclusively at shelters and PoDs. Shelters have demand only in the periods before landfall, and PoDs have demand only in the periods after landfall.

To simplify the model, we adopt the following assumptions: (i) All locations are assumed to be operational from the start of the planning horizon. (ii) The model assumes mixed commodity distribution: there is no limit on the type of commodity in the commodity flow, the only limit is imposed on the total flow capacity for each arc; (iii) The arrival of commodities to a location occurs prior to the departure of commodities from this location and the demand fulfillment.

2.2 Deterministic formulation

We begin by presenting a deterministic version of our problem for two key reasons: it provides a simpler context for introducing the logistics model, and it facilitates the transition to the discussion on the stochastic programming model.

The sets used in the proposed model are defined as follows:

$\mathcal{V}$	Set of nodes
$\mathcal{V}_0, \mathcal{V}_1, \mathcal{V}_2, \mathcal{V}_3$	Subsets of $\mathcal{V}$ including suppliers, shelters, RSAs, and PoDs, respectively
$\mathcal{A}$	Set of arcs from i to j, $(i, j \in \mathcal{V})$
$\mathcal{R}$	Set of commodities $(r \in \mathcal{R} = \{1, \ldots, R\})$
$\mathcal{T}$	Set of time periods $(t \in \mathcal{T} = \{1, \ldots, T\})$
$\mathcal{T}_1, \mathcal{T}_2$	Subsets of time periods before and after landfall, respectively (both are assumed to be 3 days)

The problem parameters are defined as follows:

d_{it}	Demand at location $i \in \mathcal{V}_1 \cup \mathcal{V}_3$ at time period $t \in \mathcal{T}$
N_{ir0}	Starting inventory of commodity $r \in \mathcal{R}$ at location $i \in \mathcal{V}$
p_i	Penalty cost of unmet demand at location $i \in \mathcal{V}_1, \mathcal{V}_3$
t_{ijt}	Time periods to travel arc $(i, j) \in \mathcal{A}$ at departure time $t \in \mathcal{T}$
K_{ijt}	Maximum commodity flow capacity on arc $(i, j) \in \mathcal{A}$ at departure time $t \in \mathcal{T}$
t_{period}	Time (in hours) in each time period
c^N_{ij}	Transportation cost of traveling arc $(i, j) \in \mathcal{A}$
c^P_{ir}	Unit procurement cost of commodity $r \in \mathcal{R}$ from location $i \in \mathcal{V}_0$
w_r, g_r	Unit weight and demand factor of commodity $r \in \mathcal{R}$, respectively
P_s	Probability of scenario $s \in \mathcal{S}$

The decision variables are defined as follows:

I_{irt}	Inventory of commodity $r \in \mathcal{R}$ at the start of time period $t \in \mathcal{T}$ at node $i \in \mathcal{V}$
U_{it}	Demand shortage at location $i \in \mathcal{V}$ at time period $t \in \mathcal{T}$ (includes unmet demand from previous time periods)
S_{it}	Demand satisfied at location $i \in \mathcal{V}$ at time period $t \in \mathcal{T}$
f_{ijrt}	Quantity of commodity $r \in \mathcal{R}$ traveling arc $(i, j) \in \mathcal{A}$ starting at time period $t \in \mathcal{T}$

The deterministic model is formulated as follows:

$$\min \sum_{i\in\mathcal{V}}\sum_{t\in\mathcal{T}} p_i U_{it} + \sum_{r\in\mathcal{R}}\sum_{t\in\mathcal{T}} \left(\sum_{i\in\mathcal{V}_0, j\in\mathcal{V}:(i,j)\in\mathcal{A}} c^P_{ir} f_{ijrt} + \sum_{i\in\mathcal{V}, j\in\mathcal{V}:(i,j)\in\mathcal{A}} c^N_{ij} f_{ijrt} \right) \tag{1a}$$

$$\text{s.t. } I_{ir0} = N_{ir0}, \forall i \in \mathcal{V}, r \in \mathcal{R} \tag{1b}$$

$$U_{it} = U_{i,t-1} - S_{it} + d_{it}, \forall i \in \mathcal{V}, t \in \mathcal{T} \setminus \{0\} \tag{1c}$$

$$U_{i0} = d_{i0}, \forall i \in \mathcal{V} \tag{1d}$$

$$\begin{aligned} I_{ir,t+1} = I_{irt} - &\sum_{j\in\mathcal{V}:(i,j)\in\mathcal{A}} f_{ijrt} \\ &+ \sum_{j\in\mathcal{V}:(i,j)\in\mathcal{A}, t-t_{jit'}+1\geq 0} f_{jir,t-t_{jit'}+1} - S_{it} g_r, \forall i \in \mathcal{V}, r \in \mathcal{R}, t \in \{0,1,\ldots,T-1\} \end{aligned} \tag{1e}$$

$$\sum_{r\in\mathcal{R}} w_r f_{ijrt} \leq K_{ijt}, \forall i,j \in \mathcal{V} : (i,j) \in \mathcal{A}, t \in \mathcal{T} \tag{1f}$$

$$f_{ijrt} \geq 0, \forall i,j \in \mathcal{V} : (i,j) \in \mathcal{A}, r \in \mathcal{R}, t \in \mathcal{T} \tag{1g}$$

$$I_{irt} \geq 0, \forall i \in \mathcal{V}, r \in \mathcal{R}, t \in \mathcal{T} \tag{1h}$$

$$U_{it} \geq 0, \forall i \in \mathcal{V}, t \in \mathcal{T} \tag{1i}$$

$$S_{it} \geq 0, \forall i \in \mathcal{V}, t \in \mathcal{T} \tag{1j}$$

The objective function of the deterministic formulation (1a) consists of two terms: the first term represents the unmet demand penalty cost and the second term represents the total logistics cost. We define the penalty parameters p_i's to prioritize commodity delivery to the most vulnerable populations. Constraints (1b) provide the initial location of commodities. Constraints (1c) define the relationship between unmet demand from the previous period, demand satisfied in the current period, and the unmet demand of the current time period, and constraints (1d) provide the initial demand. Constraints (1e) balance the flow of commodities while allowing commodities to leave the system as demand is met. Finally, constraints (1f) guarantee that the maximum arc capacity is not exceeded by limiting the total amount of commodities traveling an arc in each time period.

2.3 Two-stage stochastic programming model

In the 2SSP model we define two types of variables, state variables and local variables. The state variables represent the first-stage decisions throughout the planning horizon. The local variables represent the second-stage recourse decisions. In the context of hurricane relief logistics planning, the first-stage variables corresponds to the prepositioning of relief commodities before the hurricane occurs, i.e., the I_{irt} variables. The second-stage problem decides the allocation of relief commodities to satisfy the demand after the hurricane makes landfall and accounts for penalties due to any unmet demand, and the set of second-stage variables includes the demand shortage variables U^s_{it}, demand fulfillment variables S^s_{it}, and commodity flow variables f^s_{ijrt}, one for each scenario $s \in S$. The 2SSP model can be adapted from model (1), making one copy of second-stage constraints for each scenario $s \in S$.

Two-stage stochastic programming model

$$\min \sum_{s\in\mathcal{S}} P_s \left(\sum_{i\in\mathcal{V}}\sum_{t\in\mathcal{T}} p_i U^s_{it} + \sum_{r\in\mathcal{R}}\sum_{t\in\mathcal{T}} \left(\sum_{i\in\mathcal{V}_0, j\in\mathcal{V}:(i,j)\in\mathcal{A}} c^P_{ir} f^s_{ijrt} + \sum_{i\in\mathcal{V}, j\in\mathcal{V}:(i,j)\in\mathcal{A}} c^N_{ij} f^s_{ijrt} \right) \right) \tag{2a}$$

$$\text{s.t.} \quad I_{ir0} = N_{ir0}, \quad \forall i \in \mathcal{V}, r \in \mathcal{R} \tag{2b}$$

$$U^s_{it} = U^s_{i,t-1} - S^s_{it} + d^s_{it}, \quad \forall i \in \mathcal{V}, t \in \mathcal{T} \setminus \{0\}, s \in \mathcal{S} \tag{2c}$$

$$U^s_{i0} = d^s_{i0}, \quad \forall i \in \mathcal{V}, s \in \mathcal{S} \tag{2d}$$

$$\begin{aligned} I_{ir,t+1} = I_{irt} - &\sum_{j\in\mathcal{V}:(i,j)\in\mathcal{A}} f^s_{ijrt} \\ &+ \sum_{j\in\mathcal{V}:(i,j)\in\mathcal{A}, t-(t_{jit'}+1)\geq 0} f^s_{jir,t-(t_{jit'}+1)} - S^s_{it} g_r, \\ &\forall i \in \mathcal{V}, r \in \mathcal{R}, t \in \{0,1,\ldots,T-1\}, s \in \mathcal{S} \end{aligned} \tag{2e}$$

$$\sum_{r\in\mathcal{R}} w_r f^s_{ijrt} \leq K_{ijt}, \quad \forall i,j \in \mathcal{V} : (i,j) \in \mathcal{A}, t \in \mathcal{T}, s \in \mathcal{S} \tag{2f}$$

$$I_{irt} \geq 0, \quad \forall i \in \mathcal{V}, r \in \mathcal{R}, t \in \mathcal{T} \tag{2g}$$

$$U^s_{it} \geq 0, \quad \forall i \in \mathcal{V}, t \in \mathcal{T}, s \in \mathcal{S} \tag{2h}$$

$$S^s_{it} \geq 0, \quad \forall i \in \mathcal{V}, t \in \mathcal{T}, s \in \mathcal{S} \tag{2i}$$

$$f^s_{ijrt} \geq 0, \quad \forall i,j \in \mathcal{V} : (i,j) \in \mathcal{A}, r \in \mathcal{R}, t \in \mathcal{T}, s \in \mathcal{S} \tag{2j}$$

We applied Benders decomposition to solve our 2SSP model, designating the first-stage decisions as the master problem and the second-stage decisions as subproblems. Considering the scale of the problem, with a large number of the first-stage variables, implementing Benders decomposition proved to be quite challenging. Since the master problem initially lacks strong structural constraints on first-stage variables, the model often explores unrealistic or infeasible solutions, requiring many feasibility cuts. By tightening the feasible region through valid inequalities, we avoid generating these poor first-stage solutions, which leads to faster convergence by allowing the algorithm to focus earlier on generating optimality cuts. For instance, using the fact that the inventory at warehouses/suppliers is always expected to decrease over time as they do not receive any shipments and only dispatch commodities to other locations, while the inventory at PoDs increases before landfall, as there is no demand at PoDs prior to the hurricane's landfall, we have the following valid inequalities (3a) and (3b) corresponding to warehouses/suppliers and PoDs inventories, respectively:

$$I_{irt} \leq I_{i,t-1}, \quad \forall i \in \mathcal{V}_0, r \in \mathcal{R}, t \in \mathcal{T} \tag{3a}$$

$$I_{irt} \geq I_{i,t-1}, \quad \forall i \in \mathcal{V}_3, r \in \mathcal{R}, t \in \mathcal{T}_{bef} \tag{3b}$$

We also established lower bounds for warehouse inventory and upper bounds for PoD inventory utilizing constraints (1f). We derived additional valid inequalities to bound inventory levels based on the maximum flow capacity on outgoing and incoming arcs, leveraging constraints (1f), which limits total flow by arc capacity. For warehouses/suppliers, we imposed a lower bound on inventory by estimating the maximum amount of each commodity that could be shipped out in a given period, using arc capacity divided by commodity weight. This ensures that inventory levels cannot fall below what remains after the maximum possible outflow. For PoDs, we imposed an upper bound on inventory accumulation prior to landfall by calculating the maximum inflow capacity from upstream nodes. Inventory at PoDs is restricted to not exceed the initial inventory plus the maximum deliverable amount, again based on total arc capacity and commodity weight. Furthermore, based on the last assumption described in Section 2.1, we eliminated a set of redundant constraints that significantly reduced the number of feasibility cuts required for solving the problem with the Benders decomposition algorithm.

3. Case study

In this section, we consider a case study of the proposed hurricane logistics planning model for the study region of coastal South Carolina for Hurricane Florence 2018. The coastline is approximated on a straight line and the potential landfall location of the hurricane is assumed to be anywhere within a 200-mile extension from either endpoint of the coastline. A detailed explanation of how the hurricane's evolution is modeled as a Markov Chain is available later in this section. We define a planning horizon of six days (144 hours), three days before the hurricane's landfall and three days after. The planning horizon consists of 12 time periods in total, each being 12 hours long. We assume that the landfall time is deterministic and falls in the middle of the planning horizon ($t = 6$). At $t = 0$, the NHC's official point forecast provides the hurricane's projected track and intensity until the time of landfall.

3.1 Shelters and PoDs

We consider seven coastal counties in South Carolina located within 60 miles of the coastline, which are at risk of hurricane landfall. According to the South Carolina Emergency Management Division (SCEMD), one PoD location was designated for each county, resulting in $|\mathcal{V}_3| = 7$ PoDs in the instance. According to [3, 4], only a specific fraction of the vulnerable population is evacuated from PoDs to shelters. Furthermore, SCEMD maintains a list of potential shelter points in each county across the state. Due to the large number of shelters available and the fact that some shelters in one county are located in close proximity to one another, we apply K-Means clustering with $|\mathcal{V}_1| = 21$ to generate potential shelter locations, aggregating the total shelter capacities within each cluster.

3.2 Demand estimation

One of the most challenging aspects of disaster logistics planning is forecasting the demand for relief items. Studies have indicated that the demand for relief items is influenced by various factors, such as the hurricane's intensity and landfall location which can change over time [5]. Hurricane intensity is measured using the Saffir-Simpson Hurricane Wind Scale (SSHWS) [6], which the National Hurricane Center (NHC) employs to estimate potential damage and flooding risks. The SSHWS categorizes hurricanes into five levels based on their maximum sustained wind speeds, with Category 1 representing the lowest severity and Category 5 indicating the highest. Moreover, the location of a hurricane is determined by the latitude and longitude coordinates of its center. We use a Markov chain model to model hurricane trajectory following the approach of [7], which justifies the Markovian assumption by noting the memoryless structure of hurricane dynamics and the value of simplifying the hurricane evolution for decision-making purposes [8]. To begin, since the landfall time is deterministic in our proposed 2SSP problem, we model hurricane forecast errors based on this assumption. In this case, we generate hurricane scenarios using the NHC's track and intensity forecast error. According to [7], to account for forecast uncertainty, we apply a time series model to historical data (including both track and intensity) and produce sample paths of forecast errors based on this model. These sample paths, combined with the point forecast, generate potential trajectories of the hurricane's locations and intensities over time. The resulting wind speed associated with the intensity is indicated through the corresponding hurricane categories defined by the Saffir-Simpson (SS) hurricane wind scale and then utilized to calculate the deterministic demand after landfall in PoDs.

We suppose that the demand at each PoD during any time period is a function of hurricane's attributes (both location and intensity). We define the x- and y-axes by the coastal line (a straight line), in order to display the hurricane's track locations. The demand estimation before landfall is based on the following rules: (i) At the beginning of the planning horizon, the total population of PoDs is available; (ii) The demand is a fraction of vulnerable population that was explained earlier in the previous section; (iii) We define a lead time ($\tau = 4$), which is the number of periods until the hurricane's landfall. Hence, the demand at $t < \tau$ is zero at all PoDs. We will have a positive demand for a PoD, if its location falls within a specific threshold values in both the x- and y- axes, (x_{max}, y_{max}), from the hurricane's location [7]. After realization of demand at PoDs (equivalently, the number of people evacuated from PoDs to shelters), we distribute this demand to different shelters based on shelters' distance from PoDs. This constitutes shelter's demand in our model which only occurs before landfall. The post-disaster part of the demand happens in PoDs which is fully deterministic and can be calculated using formula: $D_{PoD} = I \cdot svi \cdot (1 - E)$, where I is the total impacted persons, svi is the social vulnerability index (SVI) of the county and E is the percentage population likely to evacuate. This amount represents the total demand after the landfall, rather than a single day's demand, based on the assumption that pick-up demand follows a normal distribution pattern. This approach models a single large pick-up where each person collects three days' worth of supplies in one visit. The majority of the demand peaks around the middle of the time window, with smaller amounts occurring at the beginning and end of the post-landfall period.

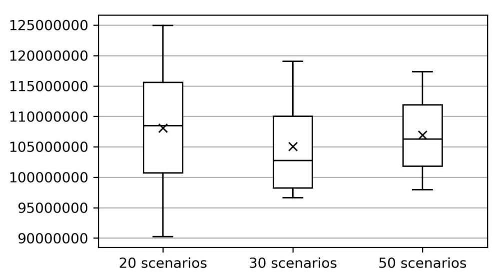

Figure 1: Illustration of the 2SSP model performance using different sample sizes

Table 1: The 2SSP model performance for different sample sizes

	Number of scenarios		
	20	30	50
Average Total Cost ($M)	1755.67	1712.05	1713.09
Std. Dev. of Total Cost ($M)	159.61	119.71	92.61
Coefficient of Variation (%)	9.09	6.99	5.41
Computational Time (s)	274	410	981

3.3 Experiment results

In this section, we show the numerical results of our model. Using an in-sample stability test for over thirty replications, we determine that $S = 50$ is a reasonable sample size, as shown in Figure 1. Furthermore, the results presented in Table 1, showing that different sample sizes in the 2SSP model result in slightly different total costs. As the sample size increases, the standard deviation of the cost reduces but the computational time increases. As we see, the average cost almost stabilizes at 50 scenarios, which is what we decide to use for the rest of our numerical experiments.

We solved both 2SSP and deterministic model (mean value problem) to show the value of 2SSP. In the deterministic model, we define the demand of relief items as the expected value of the demand values used in the 2SSP model, averaged across 50 scenarios. The deterministic model requires less time to be solved but leads to higher costs. This outcome is expected since the deterministic model incorporate only a single scenario based on the average of random realizations, which cannot provide a strong solution for state variables to handle fluctuating demand effectively. Later in the sensitivity analysis section, we can observe that the value of stochastic solutions (VSS) varies under different input parameter values.

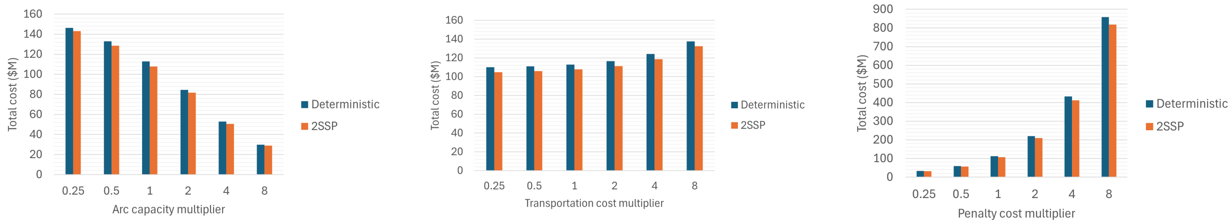

Figure 2: Comparison of total costs between 2SSP and deterministic models for different weights of input parameters.

3.4 Sensitivity analysis

In this section, we present sensitivity analysis results for different input parameters of the model including arc capacity (K_{ijt}), penalty cost (p_i) and transportation cost (c^N_{ij}). The results are presented in Figure 2, highlighting the value of stochastic programming. Specifically, we apply a multiplier of 2, 4, and 8 for the arc capacity parameters, a multiplier of 0.25, 0.5, 2, and 4 for transportation cost parameter, and a multiplier of 0.25, 0.5, 2, 4, and 8 for the penalty cost parameter. It can be seen from Figure 2 that for higher capacities, the VSS tends to decrease. The opposite behavior is observed for the other two parameters. As they increase, the 2SSP approach becomes more advantageous.

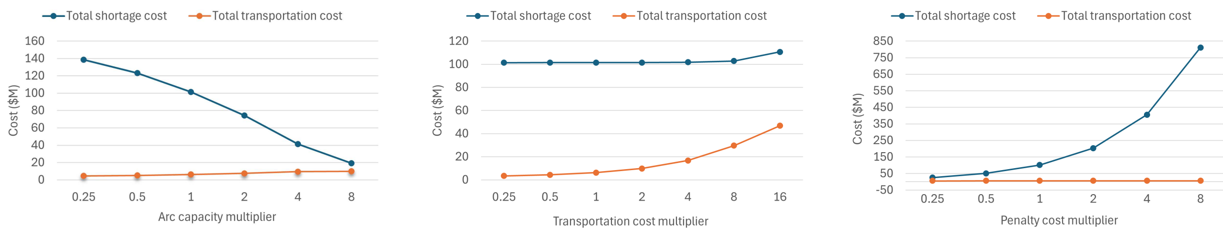

Figure 3: Comparison of total shortage cost and transportation cost in 2SSP model for different weights.

Intuitively, for the higher arc capacities, we expect that the model puts more emphasis on transporting the relief items, resulting in less shortage cost and more total transportation cost. This is validated by Figure 3. Moreover, according to this figure, increasing transportation cost multiplier leads to higher shortage costs, although the increase is relatively small. This occurs because the decision maker decides to send fewer relief items to affected locations, leading to more unmet demand. Similarly, with larger penalty cost, the model prioritizes meeting demand to decrease shortages. However, the total transportation cost appears relatively stable across this change. This initially seems counterintuitive, but it can be explained by the limited arc capacities in the network. Even as the model attempts to prioritize sending more commodities to meet demand (when the penalty is high), it is constrained by the network's arc capacities.

4. Conclusion and future research

This paper developed a two-stage stochastic multi-period network flow model for hurricane logistics planning, focusing on a case study in the state of South Carolina. We demonstrated the benefit of using this model over the deterministic approach. We also evaluated the performance of the model through a sensitivity analysis which revealed that the effectiveness of the 2SSP model improves further with different input parameters. For future research, we plan to investigate the online rolling horizon approach for the two-stage model, instead of the static policy, along with its extension to a multi-stage problem.

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