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

Abstract ID:

Abstract

In this talk, we present a logistics planning problem focused on prepositioning essential relief commodities in anticipation of a hurricane landfall. We model the problem as a service network design 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. Additionally, we implement a rolling horizon approach for adaptive decision-making as the hurricane's forecasted path and intensity are updated over time. Our numerical results and sensitivity analyses based on a case study for the state of South Carolina demonstrate the effectiveness of this adaptive, scenario-based approach compared to a deterministic service network design model.

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

1. Introduction

Hurricanes, tornadoes, and earthquakes are examples of extreme disasters that can strike a community without any notice, leaving 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, 3]. 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.

A fully adaptive multi-stage stochastic programming (MSSP) model can be employed to develop dynamic decision making, utilizing a stochastic process that represents the evolving uncertainty of hurricane characteristics over time.

However, multi-stage stochastic programming models are highly complex and require significant computational resources to solve [4]. Two-stage stochastic programming (2SSP) models may be preferred in this context due to their lower computational requirements. The solution to a 2SSP model gives a static logistics decision policy. The first-stage decisions are made prior to the realization of uncertainty, and the second-stage (recourse) decisions are made after the realization of the demand and are dependent on the first-stage decisions [5].

In this paper, we formulate a 2SSP model (static policy) 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, sensitivity analysis, and corresponding results. In Section 4, we provide a summary of the paper along with the final 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 following: links between PoDs and shelters and links where $i = j$ (self-loops). Demand occurs exclusively at shelters and PoDs. Shelters experience 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) Warehouses/suppliers and shelters locations are assumed to be operational from the start of the planning horizon and remain available for use throughout, as there are no opening decisions involved in the model. (ii) The model assumes mixed commodity distribution, where there is no limit on the type of commodity in the commodity flow, only on the total flow capacity within 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 $(t \in \mathcal{T} = \{1, \ldots, T\})$
$\mathcal{T}^{bef}, \mathcal{T}^{aft}$	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	Unit weight of commodity $r \in \mathcal{R}$
g_r	Factor of demand per commodity $r \in \mathcal{R}$
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:

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

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

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

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

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

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

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

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

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

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

The objective function of the deterministic formulation (1a) consists of two terms: the first term minimizes the penalty cost associated with the logistics plan by ensuring that the demand for commodities is satisfied as quickly as possible. The second term minimizes the transportation cost and the procurement cost (only applied to the warehouse/supplier locations) by calculating the cost of transporting and procuring commodities and the quantity of commodities moved along the arcs. This objective prioritizes commodity delivery to the most vulnerable populations. Constraint (1b) provide the initial location of commodities. Constraints (1c) and (1d) regulate demand shortages and satisfaction. Constraint (1c) defines the relationship between unmet demand, satisfied demand, and the demand of the current time period. The next constraint (1d) initializes the demand shortage. Constraint (1e) constrain the flow of commodities in the network. It balances the flow of commodities while allowing commodities to leave the system as demand is met. The next constraint (1f) guarantees that the maximum arc capacity is not exceeded by limiting the sum of all commodities traveling an arc in each time period. The final constraints (1g) through (1j) define the appropriate domains for each decision variable.

2.3 Two-stage stochastic programming model

In a 2SSP model we define two types of variables, state variables and local variables. The state variables represent the first-stage actions and define the current status of the system that carry information from the first-stage to second-stage. The local variables represent the second-stage decisions, only affecting the decisions within that stage. In the context of hurricane relief logistics planning, the first-stage problem decides the prepositioning of relief commodities before the hurricane occurs, while 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. The decision variable I_{irt} represent the inventory of commodities at its corresponding location. This variable is the state variable as it is carried over to subsequent periods in the planning horizon. At the start of the planning horizon, the initial conditions of the state variables will be defined. All other variables are local variables that only participate in the second stage of the problem.

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. The complexities we encountered in our case arose from the lack of enough constraints on the first-stage variables, aside from the initialization. As a result, the model took a significant amount of time to add feasibility cuts and make the problem feasible before it could begin working on the optimality phase. Subsequently, we imposed certain obvious constraints on the first-stage variables that did not alter the original model, aiming to improve the model's performance.For instance, the inventory at warehouses/suppliers is always expected to decrease over time, while the inventory at PoDs increases before landfall, as there is no demand at PoDs prior to the hurricane's landfall. We also established lower bounds for warehouse inventory and upper bounds for PoD inventory utilizing constraint (1f). Furthermore, based on the last assumption on 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 method.

The first-stage 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 $i \in \mathcal{V}$

The second-stage decision variables are defined as follows:

U_{it}^s Demand shortage at location $i \in \mathcal{V}$ at time period $t \in \mathcal{T}$ in scenario $s \in \mathcal{S}$ (includes unsatisfied demand from previous time periods)

S_{it}^s Demand satisfied at location $i \in \mathcal{V}$ at time period $t \in \mathcal{T}$ in scenario $s \in \mathcal{S}$

f_{ijrt}^s Quantity of commodity $r \in \mathcal{R}$ traveling arc $(i, j) \in \mathcal{A}$ starting at time period $t \in \mathcal{T}$ in scenario $s \in \mathcal{S}$

Two-stage stochastic programming model

$$\min \quad \sum_{s\in\mathcal{S}} P_s \left(\sum_{i\in\mathcal{V}} \sum_{t\in\mathcal{T}} p_i U_{it}^s + \sum_{r\in\mathcal{R}} \sum_{t\in\mathcal{T}} \left(\sum_{i\in\mathcal{V}_0, j\in\mathcal{V}:(i,j)\in\mathcal{A}} c_{ir}^P f_{ijrt}^s + \sum_{i\in\mathcal{V}, j\in\mathcal{V}:(i,j)\in\mathcal{A}} c_{ij}^N f_{ijrt}^s \right) \right) \tag{2a}$$

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

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

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

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

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

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

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

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

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

3. Case study

In 2018, Hurricane Florence made landfall in both North Carolina and South Carolina. In this section, we address a hurricane logistics planning for a study region that includes the coastal are of South Carolina, assuming a deterministic landfall time. 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), 3 days before the hurricane's landfall and 3 days after the hurricane's landfall. 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 ($t = 5$). 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

Hurricanes making landfall outside the study region generate zero demand at all PoDs. We consider seven coastal counties in South Carolina, situated within the 60 miles of the coastline, which are at risk of hurricane landfall. The locations of PoDs are approximated by projecting the geographical coordinates of all vulnerable areas onto the coastline. According to the South Carolina Emergency Management Division (SCEMD), one PoD location was designated for each county, resulting in $|\mathcal{V}_3| = 7$, representing the PoDs in our model. According to [6, 7], 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. Since the number of these shelters is too large to consider each one as an independent shelter and also 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 shelters, aggregating the 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 [8]. Hurricane intensity is measured using the Saffir-Simpson Hurricane Wind Scale (SSHWS) [9], 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 follow [10] and model the evolution of the hurricane's attributes following a Markov chain. 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 [10], 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 [10]. 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 the following equation:

$$D_{PoD} = I \cdot sv \cdot (1 - E) \tag{3}$$

where I is the total impacted persons, sv 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.

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 different total costs. It is obvious that larger number of scenarios brings us closer to the true total cost. As the sample size increases, the standard deviation of the

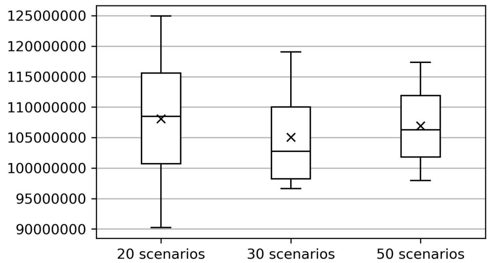

Figure 1: Illustration of the 2SSP model performance using different sample sizes

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

	Number of scenarios		
	20	30	50
Average Total Cost ($M)	108.09	105.05	106.91
Std. Dev. of Total Cost ($M)	9.845	7.342	5.731
Coefficient of Variation (%)	9.11	6.99	5.36
Computational Time (s)	72	234	2001

cost reduces but the computational time increases. As you can see in the table, the average cost almost stabilizes at 50 scenarios. Hence, the results showing in the following sections used 50 scenarios in 2SSP model.

We solved both two-stage stochastic programming 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 programming changes under different input parameter values.

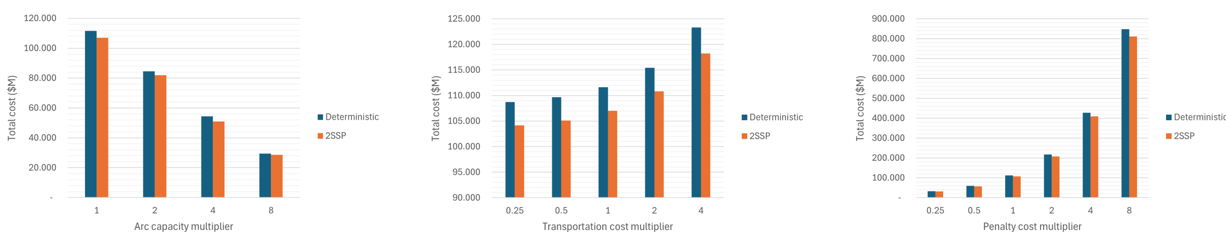

Figure 2: Comparison of total costs between 2SSP and deterministic models for different weights of input parameters.

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_{ij}^N). The results are presented in Figure 2, highlighting the differences between the 2SSP model and the deterministic model as well, which demonstrate the value of stochastic programming. We begin by analyzing the parameters set in a range between 0.25 to 8 times the baseline value. In this comparison, lower multipliers for the arc capacity were not considered due to the weak performance of the deterministic model, which sometimes resulted in infeasibility. We can observe from Figure 2 that for higher capacities, the VSS tends to decrease, showing that the 2SSP model may become less effective under higher capacity levels. The opposite behavior is observed for the other two parameters. As they increase, the 2SSP approach becomes more advantageous. It is important to highlight that, across all evaluations, the deterministic model shows a computational time enhancement of 20-50 percent compared to the 2SSP model. However, the results indicate that this approach is not as strong as the 2SSP model.

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, since we have limit capacities for transportation, total shortage costs still rise, as unsatisfied demand cannot be fully eliminated. Furthermore, total transportation costs remain stable due to aforementioned capacity limits.

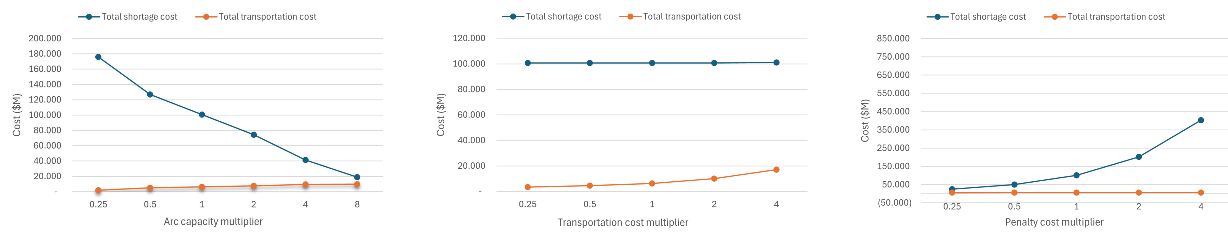

Figure 3: Comparison of total shortage cost and total transportation cost in 2SSP model for different weights of input parameters.

4. Conclusion and future research

This paper developed a two-stage stochastic service network design 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.

References

[1] South Carolina Emergency Management Division (SCEMD), “South Carolina Hurricane Plan," [Online]. Available at: https://www.scemd.org/em-professionals/plans/south-carolina-hurricane-plan.

[2] Guardian, 2012, “How pre-positioning can make emergency relief more effective," [Online]. Available: `http://www.guardian.co.uk/global-development-professionals-network/2013/jan/17/prepositioning-emergency-relief-work`.

[3] Duran, S., Gutierrez, M. A., and Keskinocak, P., 2011, “Pre-positioning of emergency items for CARE international," Interfaces, 41(3), 223-237.

[4] Shapiro, A., 2021, “Tutorial on risk neutral, distributionally robust and risk averse multistage stochastic programming," European Journal of Operational Research, 288(1), 1-13.

[5] Birge, J. R., and Louveaux, F., 2011, *Introduction to stochastic programming*, Springer Science & Business Media.

[6] Simon, E., 2024, “Modeling of multi-period disaster logistics planning in the state of South Carolina," Master Thesis at Clemson University.

[7] Cutter, S. L., Emrich, C. T., Bowser, G., Angelo, D., and Mitchell, J. T., 2011, “2011 South Carolina hurricane evacuation behavioral study," Hazards and Vulnerability Research Institute, Department of Geography, University of South Carolina.

[8] Kirac, E., and Milburn, A. B., 2018, “A general framework for assessing the value of social data for disaster response logistics planning," European Journal of Operational Research, 269(2), 486–500.

[9] Taylor, H. T., Ward, B., Willis, M., and Zaleski, W., 2010, “The Saffir-Simpson hurricane wind scale," Atmospheric Administration, Washington, DC, USA.

[10] Bhattarai, S., and Song, Y., 2024, “Multistage stochastic programming for integrated network optimization in hurricane relief logistics and evacuation planning," Networks, 85(1), 3-37, 2024.