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Modeling of Multi-Period Disaster Logistics Planning in the State of South Carolina

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MODELING OF MULTI-PERIOD DISASTER LOGISTICS PLANNING
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ABSTRACT

South Carolina is one of the most vulnerable states in the United States to the impact of hurricanes. Currently, when threatened with a natural disaster such as a hurricane, the state government makes many vital decisions based on knowledge and experience. In this study, the distribution of disaster relief commodities to meet immediate needs is analyzed through two models for the case of South Carolina to generate an optimal logistics strategy that considers the social vulnerability of affected populations. The first model is a multi-objective pre-disaster logistics model that uses a four-index formulation for the multiple trip vehicle routing problem. The second model is a multi-objective pre- and post-disaster time-expanded network flow model with detailed operational-level decisions for the overarching tactical planning decisions, which allows the model to act as an optimization-based simulator. Sensitivity analyses were conducted to determine optimal conditions for the cases used and to analyze the effects of different assumptions on the resulting logistics plan. This paper presents models that optimize scenario-dependent logistics plans, visualize logistic solutions, and suggest alternatives to some aspects of the government's current logistics plan to aid in the efficient distribution of life-saving supplies.

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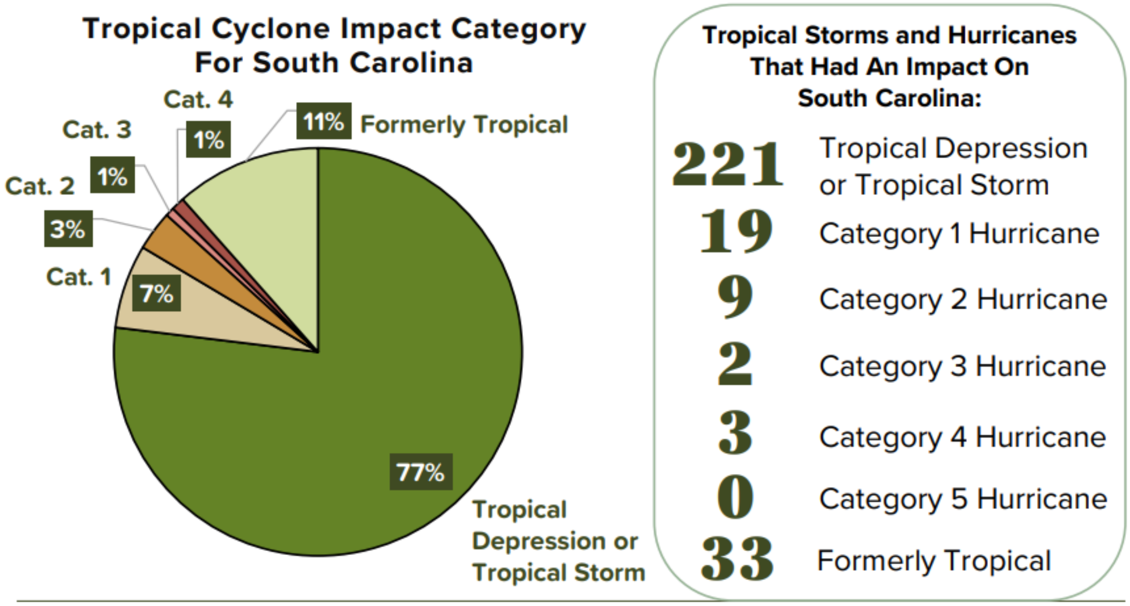
CHAPTER ONE

INTRODUCTION

Between 1851 and 2023, 286 tropical cyclones impacted the state of South Carolina, five of which were classified as category 3+ (1851-2023 is the period of record) [1]. The state's 187-mile coastline leaves it highly vulnerable to hurricanes and tropical storms [2]. South Carolina is ranked 5^{th} among US states for the most hurricane impacts over recorded history, making hurricane planning a critical issue in the state [1]. The state government acknowledges its responsibility to protect its citizens and has a variety of plans that "establish the procedures by which the State will coordinate pre- and post-incident logistics operations including needs assessment, receiving supplies, staging/warehousing supplies, supply distribution, ordering, processing, and transporting supplies requested by county emergency management departments, State agencies and other response and relief entities supported by the State" [3].

Logistics operations related to a disaster are coordinated by the South Carolina Emergency Management Division (SCEMD) and start before a known event or immediately following the impact of an unexpected incident [3]. Our research team has partnered with SCEMD to model their decision-making process. The goals of this partnership include evaluating current plans and solution visualization.

Figure 1.1: Tropical Storms and Hurricanes that Impacted South Carolina [1]



Inadequate planning can have various consequences, including loss of lives and waste of resources. A recent example of logistics mismanagement was FEMA's distribution process in response to Hurricanes Irma and Maria, where the organization lost visibility on approximately 38% of its commodity shipments, worth approximately $257 million [4]. When commodities were successfully delivered, they took an average of 69 days to reach their destinations [4]. This mismanagement happened during a disaster scenario, but the causes can be attributed to a lack of planning and preparation of the processes that take place in a disaster of such magnitude [4]. Historically, South Carolina has been able to save lives through the proper execution of thoroughly vetted logistics plans [5] [6].

South Carolina Logistics Plan Elements Pertaining to Disaster Events

South Carolina's logistics plan includes information on regional staging areas, warehouses, demand, procurement of resources, and distribution.

Regional Staging Areas (RSAs)

Regional staging areas (RSAs) are locations determined by SCEMD where commodities will be prepositioned before being distributed to individual points of demand [3]. The placement of RSAs is dependent on which regions are most likely to be impacted by the event and in proportion to the scale of the event [3]. Bills of Lading and other shipping documentation must be completed as resources enter and leave an RSA, the signing and processing of which will be handled by the State Emergency Operations Center (SEOC) Resource Coordinator [3].

SCEMD Warehouses

SCEMD has two warehouses that store, receive, and distribute resources before, during, and after an incident [3]. The first primary warehouse is located in Winnsboro, SC and contains disaster meals, water, sandbags, and tarps (the SCEMD team has indicated they do not regularly keep an inventory of perishable goods) [3]. The Winnsboro warehouse has 43,000 sq. ft. and is estimated to store 1,200 pallets, according to the SCEMD DMP 2023 Workbook [3]. Six loading docks and three forklifts are available at the Winnsboro location, but there are no permanent warehouse staff members (warehouse management and support staff are required for operation after activation) [3]. A secondary location in Fairfield County is available as necessary and used upon request, providing storage space for up to 2,400 pallets [3]. The second primary warehouse is in Prosperity, SC and holds PPE for public health emergencies.

Cots have different storage considerations as the majority are not state-owned. There are 4,000 cots stored at the McEntire Joint Base outside of Columbia [2]. These 4,000 cots are primarily distributed to Group 1 shelters by the South Carolina National Guard [2]. There are another 8,000 cots already in the state, which are part of the American Red Cross Regional Stock [2]. These 8,000 cots are staged in four hurricane regions (Myrtle Beach area, North Charleston, Jasper County, and the Upstate), and the American Red Cross leads their distribution in the event of a disaster [2]. While the SCEMD team does not play a direct role in cot distribution, they are responsible for identifying resource gaps and coordinating the distribution [2].

Demand

Counties conduct their own damage assessments and report damage and population affected to SCEMD when submitting resource requests [3]. Requests are submitted to the SEOC Supply Unit, and specify the resources and quantities needed along with the delivery locations, delivery timelines, and Points of Contact regarding the delivery [3]. South Carolina takes a cutting-edge approach to disaster recovery demand fulfillment by considering social vulnerability and income level throughout the entire logistics process as socioeconomic variables can indicate a community's ability to prepare for, respond to, and recover from natural disasters [5]. Holistic social vulnerability considers a variety of factors, including age (being over 65 or having children under five contributes to vulnerability), social status, race, wealth (level of poverty), ethnicity, gender, state of housing (focused on transitional housing and homelessness which increases vulnerability), and unemployment [5] [6].

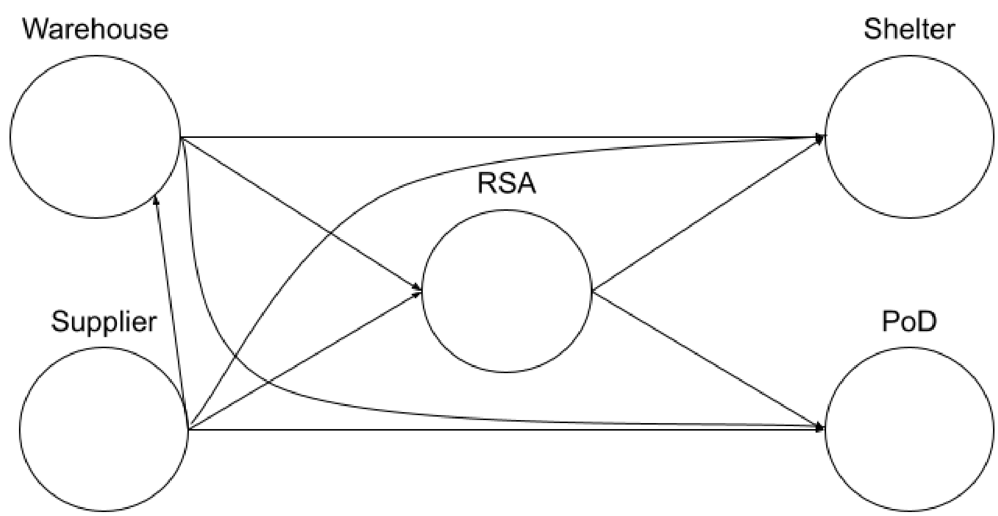
Procurement of Commodities

Before purchasing commodities, the SEOC Supply Unit will check if the commodity is available in their warehouses or through donated goods [3]. If purchasing the commodity requested, the Logistics Chief or their designee will use pre-existing contracts when possible [3]. These contracts are not public, but SCEMD has provided some examples of suppliers.

Commodity Distribution

The distribution of commodities follows the flow depicted in Figure 1.2. Counties are responsible for unloading, delivery documentation, and distribution of supplies at the demand nodes (shelters and points of distribution (PoDs)) [3].

Figure 1.2: Commodity Distribution Flow



South Carolina's Policy at Demand Points

Demand occurs at shelters and points of distribution (PoDs). Shelters are designated for evacuees or survivors to eliminate or lessen immediate threats to their safety [7] [8]. PoDs provide life-saving commodities such as food (in the form of MREs) and water to the vulnerable population that does not evacuate, commonly referred to as the stay-back population.

Shelters

South Carolina Code of Laws states that counties are responsible for developing and implementing a sheltering plan [7]. Shelter locations are determined prior to the threat of a disaster by a team of organizations, which include County Emergency Management, SCEMD, Emergency Support Function (Mass Care (ESF-6)), and the American Red Cross [7]. Locations selected as shelter candidates are generally along evacuation routes, have a large capacity, are accessible, and have a backup power source [7]. Shelters are grouped into tiered opening levels where groups are sequentially opened [7]. Additional shelters are opened based on the "percentage full" of current open shelters, where, as a group of shelters reaches 75% of its capacity, the next group will open [7].

The estimated number of evacuees guides the shelter space planning requirements and is based on the calculated vulnerable population. The vulnerable population includes residents and tourists within a Category 5 storm surge inundation area [7]. The Army Corps of Engineers is responsible for completing the Hurricane Evacuation study, which determines the shelter requirements for vulnerable populations [7]. The vulnerable population, specifically in the Coastal Hurricane Region of the state, is dynamic and generally increasing [7]. This increase is caused by a rise in coastal population and a growing percentage of the population living in vulnerable structures [7].

In South Carolina, the emergency capacity for hurricane evacuation shelters is calculated using 20 sq. ft. per person, but for shelters extending their operation beyond 72 hours, 40 sq. ft. per person is required, causing a population shift [7]. According to the SCEMD team, the aim is to supply three days' worth of supplies as a standard, and there is an explicit effort to close shelters as rapidly as possible. This desire to rapidly close shelters is because many are schools, and the ongoing shelter (and PoD) operations have a negative impact on the local economy during recovery.

The American Red Cross has generated a list of standards to be considered for hurricane evacuation shelter selection, which is followed by the state of South Carolina [7]. The standards address risks linked with hurricane-associated hazards, which include surge inundation, rainfall flooding, and high winds [9]. Other considerations include whether hazardous materials are present and the safety criteria of the interior of the building [9]. When selecting locations, the Red Cross encourages "least-risk decision making" and insists safety is the primary consideration [9]. Evaluating a potential shelter requires the identification of a viable site, execution of a risk assessment on the site, assessment of the facility by a structural engineer, and completion of a Red Cross Facility Survey [9].

Points of Distribution (PoDs)

According to conversations with the SCEMD team, counties are responsible for commodity allocation and distribution of life-saving supplies, such as food and water, at points of distribution (PoDs) to the stay-back population. Counties determine how many days of materials will be distributed to an individual, the locations of PoDs, and the quantity of PoDs within their jurisdiction.

SCEMD uses daily reports from affected counties to determine PoD locations, daily commodity distribution quantities, and shipment deliveries [3]. SCEMD processes PoD requests in order of priority and provides the county with the shipment's departure and expected arrival time [3]. As previously stated, counties are responsible for unloading the material from the shipping vehicle, distributing the items, and completing delivery documentation [3].

CHAPTER TWO

LITERATURE REVIEW

There is a variety of literature on disaster logistics with a considerable breadth of cases assessed. Literature related more generally to modeling techniques was also reviewed, including vehicle routing, time-expanded networks, and fairness in modeling.

Optimization Literature Related to Disaster Relief Logistics

Emergency Supply Pre-positioning

Rawls and Turnquist (2010) showed a two-stage stochastic mixed integer problem with the goal of providing an emergency response pre-positioning strategy for disaster threats [10]. This paper's objective statement minimizes the expected costs over all scenarios dependent on the selection of the pre-positioning locations and their size, commodity procurement, shipments of supplies to demand points, unmet demand penalties, and holding costs for unused materials [10]. Similarly, Salmerón and Apte (2010) proposed a two-stage stochastic model to guide pre-disaster planning [11]. The first objective of the model is to minimize the expected casualties of individuals requiring emergency evacuation groups and those who choose not to evacuate, with the second objective of minimizing the unmet needs of individuals who choose to evacuate [11]. This paper has a further emphasis on different methods of transit than other papers and includes a unique decision variable that determines how many square feet of aircraft ramp space should be created [11].

Alem et al. (2021) examine how social vulnerability can be used to effectively meet needs within disaster preparedness and logistics modeling [12]. This paper focuses on warehouse inventory and capacity with an objective statement to maximize the effectiveness of the disaster response [12]. This paper stands apart from other literature as a social vulnerability index (SVI) was used to evaluate the extent to which the logistics plan covers as many victims' needs as possible [12].

Robust Optimization Modeling

Robust optimization was used in various papers to model disaster logistics planning under uncertain demand represented through scenarios. It was used by Avishan et al. (2023) to maximize total utility gained by relief logistics teams, by Ben-Tal et al. (2011) to decide emergency response and evacuation traffic flow with time-dependent demand uncertainty, and by Wang and Paul (2020) to determine optimal deployment time before deciding optimal PoD locations, stockpile capacities, and network flow [13][14][15].

Case Studies

Case studies based on real-world logistic problems related to natural disasters can be seen in most papers on this subject. Case studies related to the papers discussed in this literature review are briefly overviewed here.

The Rawls and Turnquist (2010) pre-positioning paper includes a case study on the Southeast United States due to the Atlantic Basin's frequent hurricanes [10]. The Alem et al. (2021) paper on humanitarian supply chain focuses their case study on Brazil, as the country struggles with unequal distribution of commodities and social inequalities, which push the most vulnerable to risky areas or informal settlements [12]. The robust optimization papers used the cases of the Van earthquakes that hit Turkey in 2011 and hurricane evacuation on the Cape May peninsula in New Jersey [13] [14].

There are many other cases examined in other papers beyond those included in this review that relate to natural disaster logistics planning, but none that explicitly focus on the state of South Carolina.

Vehicle Routing Problem

The Vehicle Routing Problem (VRP) minimizes the total cost of travel by determining efficient vehicle routes, where a route is a trip that begins and ends at the depot and visits a subset of the customers in a specified sequence [16]. Each customer or demand node is assigned to exactly one of the vehicle routes, meaning that customer demand cannot exceed vehicle capacity [16].

Split Delivery Vehicle Routing Problem

The Split Delivery Vehicle Routing Problem (SDVRP) has an objective of minimizing the total traveling costs of vehicles and is commonly used in commercial and humanitarian logistics [17][18]. In SDVRP, a fleet of vehicles with identical capacity serves a set of customers with a given cost to travel between nodes [17]. A customer's demand can be greater than the vehicle capacity, meaning a demand node may need to be visited by multiple vehicles, and its demand may be split among the vehicles [17]. If beneficial, demand may be split among different vehicles, even if the demand is not greater than the vehicle capacity [17]. The cost of SDVRP is reduced compared to the Vehicle Routing Problem, where a single visit to each demand node is imposed [17].

A Branch and Cut algorithm can be used to calculate the bounds of an SDVRP. Munari and Savelsbergh (2022) introduced two Branch and Cut formulations that use vehicle indexing: MTZ and Commodity-Flow [18]. Achietti et al. (2014) also presents two formulations referred to as compact formulations because they are not based on variables indexed by vehicle or by the visit number [17]. These compact formations are titled Two-Index Vehicle Flow and Single-Commodity Flow [17].

Multiple Trip Vehicle Routing Problem

The multiple trip vehicle routing problem (MTVRP) is a vehicle routing problem that allows for multiple trips when considering continuous time [19]. A trip or loop is a sequence of visits to demand nodes preceded and followed by a stop at a depot or warehouse [19]. Sequences of trips performed by the same vehicle are referred to as journeys [19].

The most common formulation across previous literature is the four-index formulation [19]. This formulation allows for the time of each trip and each journey to be constrained [19]. In this model, decision variables related to the arc travel decision or the load in a vehicle when traveling an arc are indexed over the vehicle, trip, and two nodes which travel occurs between[19].

Time-Expanded Network

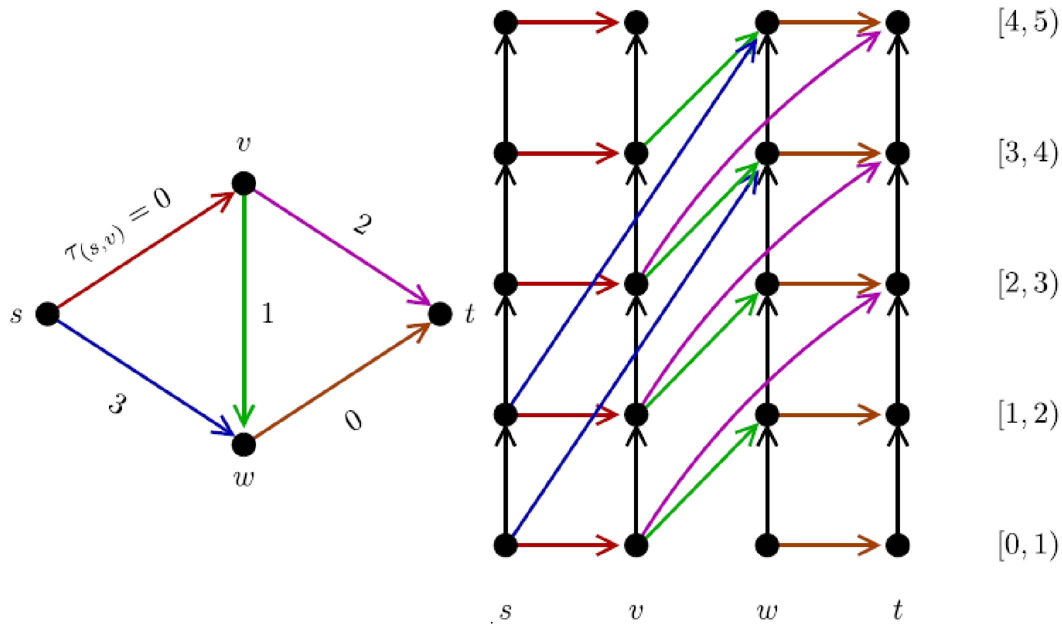
Ford and Fulkerson (1958) published Flows in Networks, a research study on time-expanded networks, and more specifically, the maximal flow problem and the minimum cost flow problem. For a time-expanded network, time is discretized, meaning the planning horizon must be partitioned into discrete time intervals [20]. The shorter the interval selected, the higher the quality of the approximation of the continuous-time problem, but a shorter time interval also increases the computational difficulty of the problem [20].

The benefits of a time-expanded network are that it can model time-dependent arc capacities, costs, and transit times [21]. In their paper, Ford and Fulkerson assume commodity flow originates from one source node and flows through transshipment nodes to a sink node where all commodities are destined [22].

Minimum Cost Flow Problem

The objective of the minimum cost network flow problem is to, as the title conveys, minimize the cost of flows over time [21]. An example of a time-expanded network can be seen in Figure 2.1. On the left of this figure is network A, with a node set of N={s,v,w,t} and listed travel times. The right side of the figure shows the time-expanded network A_T where the set of time periods is T=$\{0,1, \dots 4\}$. The time-expanded network has a node for each interval [t, t+1) where $t \in T$. The colored arrows in Figure 2.1 correlate between networks A and A_T, and in the depiction of A_T, show when arrival occurs based on the time period of departure.

Figure 2.1: Time Expanded Network Example [21]



Fairness in Modeling

Fairness and utility are generally considered conflicting objectives in operations research, specifically when modeling a process that will be paid for by taxpayers [23]. Fairness, or equity, maximizes the minimum utility of a population, where utility is a parameter that assigns the usefulness of an action in aiding an individual or group of individuals [23]. Models focusing on utilitarianism maximize the total utility of the aid, regardless of differences in the amount of aid provided to each individual [23]. Focusing on utility generally attempts to achieve the “most good” or seek the most benefit from an investment [23].

Singh’s 2019 paper discusses how fairness can be implemented when considering scarce resources. In this model, if there is less than 100% coverage for any individual or population, that user or population should be allocated what they are considered eligible to receive [24]. In a scenario of scarce resources, the sum of demand (x_{ik}) for resources ($k \in K$) over individuals seeking that resource ($i \in I_k$) is less than the total number of resources available (b_k), while in a scenario with abundance, the sum of demand equals the total resources [24]. While there is abundance, the entity of demand is met, while scarcity generally allows for only a proportion (y_i) of demand to be met [24].

$$\text{Abundant Scenario: } \sum_{i \in I_k} x_{ik} < b_k \text{ and } y_i = 1 \; \forall i \in I_k$$

$$\text{Scarcity Scenario: } \sum_{i \in I_k} x_{ik} = b_k \text{ and } y_i < 1 \; \forall i \in I_k$$

Singh's paper also discusses the difference between priority, fairness, balance, and proportional fairness. Priority occurs when the weight assigned to a population's proportion of demand met is higher for one population ($y_{i'}$) than another (y_i)[24]. Fairness occurs when appropriate priority is achieved and $y_{i'} > y_i$ [24]. Balance happens when the two populations' marginal losses are inversely proportional to their weights [24]. Finally, Singh's definition of proportional fairness occurs when both populations have a need for the same resource ($k \in K_i \cap K_{i'}$) and both are provided some of that resource while their demand is not completely fulfilled ($y_{i'} < 1$ and $x_{i'k} > 0$ while $y_i < 1$ and $x_{ik} > 0$) [24]. Population i' has a justifiable reason for complaint when considering proportional fairness if i' has less than 100% coverage, i has received a positive allocation of a resource shared with i', the coverages are balanced, and i' did not receive any of the shared resource or i achieved full coverage [24].

CHAPTER THREE

A PRE-DISASTER LOGISTICS PLANNING MODEL FOR HURRICANE EVACUATION SHELTERS IN SOUTH CAROLINA

This chapter discusses the assumptions, data inputs, and formulation of a pre-disaster logistics model and includes a sensitivity analysis for a scenario where a Category 3 hurricane hits the entire coast of South Carolina. The model was built using a four-index formulation for the multiple trip vehicle routing problem, where priority for life-saving commodities is given to the most socially vulnerable. The primary purpose of the multi-objective model is to minimize the penalty cost of the logistics plan. Minimizing financial costs and the time consumed are the secondary objectives.

Data Collection and Formulation for Input

Data was collected from federal and state government documents and resources. The South Carolina Emergency Management Division (SCEMD) has also supplied their data and provided insights into the current demand forecasting process and decision-making procedure.

Discrete Shelter Demand

The first step to determining the shelter demand was to find the total impacted persons for each county, taken from the listed population in the 2020 census [25]. Next, the number of persons needing essential commodities is calculated by multiplying the number of impacted persons by the social vulnerability index (SVI) of the county, which was collected in 2020 and reported by the Center for Disease Control and the Agency for Toxic Substances and Diseases Registry [26]. The SVI value used for the calculations is referred to as “RPL Themes,” which represents the overall percentile ranking for SVI, according to documentation. SVI for the counties considered in this model can be seen in Table 3.1. The number of persons affected in shelters was then calculated by multiplying the persons needing basic commodities by the regional percent likely to evacuate and the regional percent likely to evacuate to a public shelter (region assumptions can be seen in Appendix A, Figure A-1) (percentage values by conglomerate listed in Appendix A, Table A-1) [27]. The number of emergency workers must also be calculated to determine the total need at the shelters. Emergency workers required per shelter was calculated as done in the SCEMD DMP 2023 Workbook, which specifies 2.5 workers are required per 100 displaced households, or one worker per 100 persons affected in shelters (a household is assumed to be 2.5 people). The sum of the number of emergency workers and the number of persons affected in shelters is the worst-case deterministic demand for hurricanes category 3+. The entire calculation of demand can also be seen in Equation 3.1.

Table 3.1: SVI for Counties Considered [26]

County	SVI
Berkeley	0.2444
Charleston	0.1111
Colleton	0.7111
Dorchester	0.3111
Georgetown	0.2889
Horry	0.3556
Jasper	0.8222

Equation 3.1: County Shelter Demand Calculation

$$D_c = T\ p_c\ E_{PS}\ E\ (1 + R)$$

where:
D_c: County demand for shelters
T: Total impacted persons [25]
p_c: SVI of county (SVI is interpreted as the percentage of vulnerable population) [26]
E_{PS}: Percentage of population likely to evacuate to a public shelter [27]
E: Percentage of population likely to evacuate [27]
R: Ratio of emergency workers (1/100)

Demand is calculated for each county but will be satisfied at shelter locations. Shelters within a county can fulfill the demand for that county, but demand is not assigned to shelters individually.

Truck Capacity in Kits

Truck capacity was determined in kits, which contain everything an individual would need to survive in a shelter for three days. This three-day assumption is because, after 72 hours, persons in the shelter require twice as much space, changing the entire sheltering strategy and creating a population shift [7]. According to the SCEMD DMP 2023 Workbook, a person requires three liters of water per day, two meals per day, two blankets, and one cot, so a kit contains nine liters of water, six meals, two blankets, and one cot. Each unit of demand (a person arriving at a shelter) requires one kit (materials to survive for three days) to be considered satisfied.

The truck capacity was calculated by looking at the percentage of the truck each pallet of a commodity uses. These percentages were correlated to how much demand that space could then satisfy. For example, one pallet of water takes up 3.85% of a truck and can serve 112 people. An ideal ratio of the four commodity pallets was determined heuristically to find that 768 kits fit on a truck. The values used for this calculation were provided in the SCEMD DMP 2023 Workbook and can be seen, along with calculated kit values, in Table 3.2 (it is important to note that SCEMD does not have to meet truck weight restrictions during emergency scenarios).

Table 3.2: Kit Calculations per Truck for Three Day Supply

Commodity	Pieces per Pallet	Pallets per Truck per Commodity	People Served per Truck	Percent of Truck Used by Commodity
Water	1008 L	7	784	26.92%
Meals	576 MRE	8	768	16.67%
Blankets	120 units	13	780	25.00%
Cots	48 units	16	768	30.77%
		Sum: 44	Minimum: 768	Sum: 99.36%

Network Calculations

The time and distance between the shelters and the starting warehouse in the network as well as the shelter's capacity were also required as an input. Firstly, a reference file was created with each shelter's county, name, address, coordinates, and capacity level. This data was found using Annex H to SCEMD's Hurricane Plan General Population and Shelter Management [7]. The distance and time between all nodes in the network were calculated using the Google Map API.

Assumptions

Two types of assumptions are made to model this scenario: model constraint and value. The model constraint assumptions take the form of assumptions modeled through a constraint or are assumptions involved in the overall formulation of the model. The value assumptions are parameter values input into the program and are easily adjustable.

Model Constraint Assumptions

The first model constraint assumption is that sourcing and packaging have already occurred, which means the model only considers routing, delivery, and shelter opening decisions. It is also assumed that a perfect storm forecast is provided, and the affected population's decision to evacuate to a shelter can be perfectly predicted, thereby allowing the model to be deterministic. The next assumption is that delivery quantities must meet shelter capacity, which in some cases exceeds demand, and that there are an unlimited number of kits to distribute located at McEntire Joint Base.

The financial cost is modeled as a sum of the delivery cost and the cost of opening a shelter. The delivery cost is based on the fuel and personnel costs associated with the determined logistics plan. The cost of opening a shelter is modeled as the salary of the required emergency workers (based on the capacity of the shelter) for the period beginning when the decision is made to start the delivery process and ending when the disaster strikes (this period of time is a decision variable).

It is assumed that the trucks will make "loops" over the delivery strategy following the four-index formulation of the Multi-Trip Vehicle Routing Problem. The loops occur when the truck returns to the warehouse to change shifts or reload with more kits.

The final notable assumption within the model is that deliveries can only be made to open shelters and that only one truck may visit each shelter. With the given data, some shelters had larger capacities than the truck size, meaning the shelter capacity demand for kits is greater than the number of kits that could fit on a truck. In these cases, the shelters are "split," meaning duplicate shelters are made with the exact truck quantity, and the difference is put in the original shelter. For example, if a shelter has a capacity of 2,000, it would be split twice, resulting in two "new" shelters with a capacity equivalent to the truck capacity of 768, and the original shelter will remain with an adjusted capacity of 464 ($2000 - 2(768) = 464$). The "new" shelter duplicates would be marked with no distance from the original location.

Value Assumptions

The penalty cost is a vector of values assumed to be the social vulnerability index (SVI) per county. It is used in the objective to encourage the needs of the most vulnerable to be met first but does not account for fairness between counties (SVI of relevant counties can be seen in Table 3.1).

The model also requires assumptions for the trucking aspect of the delivery of the kits. The first assumption is that four workers would be on each truck, and the workers could not work shifts of more than 10 hours. It is also assumed that it would take 30 seconds to load and unload each kit and that a truck would spend 30 minutes per stop on paperwork.

Value assumptions were also made to calculate and limit the financial cost of delivery. The salary assumption is $15 per hour for emergency workers while working either in a shelter or on a truck. The next cost assumption is that the truck fuel used for delivery costs $0.1 per mile.

Shelters have different priority levels, so the state would prefer to open level one shelters before opening level two shelters. The available data contains five levels of shelters [7]. It is assumed that, within a county, the previous level must have 70% of shelters open to open shelters in the next level.

Some assumptions have been discussed in the previous data collection section, such as the use of a kit as a unit that can provide for an individual's needs while at a shelter for three days. The budget of time is assumed to be three days due to the sheltering policy's reallocation of space [7]. Other previously described assumptions include the demand calculation and truck capacity. The demand calculation is a multiplication of the total impacted people, the SVI, the percentage of the population likely to evacuate, and the percentage of the population likely to go to a public shelter (seen in Equation 3.1). The truck capacity was determined to be 768 kits using Table 3.2, given the three-day supply period.

Defining the Network

The network nodes are in set V, with the base location being the cot storage location near Columbia, McEntire Joint Base, which is called location 0. The set V_0 is the set including only the shelters (all nodes but the base location). Location 0 in set V is the source node for the entire network and the sink nodes are the set V_0. The model allows for travel between all nodes with arc set A of links (i,j) when i,j $\in$V.

Prepositioning Logistics Model

This section introduces the prepositioning optimization model for shelter logistics planning.

Sets:

$c \in C$	Set of counties
V $i, j \in V$	Set of shelters with base location 0 (SCEMD Warehouse)
$(i, j) \in A$	Set of links from i to j ($i, j \in V$)
V_0	Set V not including location 0; $V_0 = V \backslash \{0\}$
$V(c) \subseteq V$	Set of all shelters in county $c \in C$
$k \in K$	Set of trucks
$r \in R$	Set of loops available to trucks
$n \in N$	Set of shelter priority levels

Parameters:

q_i	Full capacity at each shelter $i \in V$
T^{bef}	Time before landfall (Assumed 3 days)
d_c	Demand of county $c \in C$
p_c	Penalty cost of unfulfilled demand per county $c \in C$
B^{max}	Monetary budget limit
t_{ij}	Time to travel link $(i, j) \in A$
e_{ij}	Distance to travel link $(i, j) \in A$
t^u	Unit time to unload or load truck (Assumed 30 sec per kit)
t^p	Unit time to compete paperwork at stop (Assumed 30 min per stop)
w^k	Number of people on truck $k \in K$ (Assumed 4 people)
Q	Truck capacity (Assumed 768 kits)
l^{max}	Maximum loop length in time (Assumed 10 hrs.)
m^s	Salary cost (Assumed $15 per hour)

m^f Fuel cost (Assumed \$0.10 per mile)

w^c Weighted financial cost

w^t Weighted time

u_{in} Binary: 1 if shelter $i \in V_0$ is in priority level $n \in N$
0 otherwise

G Priority between levels of shelters (Assumed 70%)

Decision Variables:

x_{ijr}^k Binary: 1 if truck $k \in K$ travels arc $(i, j) \in A$ on loop $r \in R$
0 otherwise

y_{ir}^k Binary: 1 if truck $k \in K$ reaches node $i \in V$ on loop $r \in R$
0 otherwise

f_{ijr}^k Load on truck $k \in K$ while traveling arc $(i, j) \in A$ on loop $r \in R$

z_i Binary: 1 if shelter $i \in V_0$ is open
0 otherwise

t Amount of time delivery optimization takes

t^k Amount of time each truck $k \in K$ requires

b Amount of money delivery strategy requires to complete

s_c Demand shortage in county $c \in C$

Formulation:

$$min \sum_{c \in C} p_c\, s_c + b \cdot w^c + t \cdot w^t \tag{1}$$

s.t.

$$y_{ir}^k = \sum_{j \in V \ \ j \neq i} x_{ijr}^k \ \ \forall k \in K,\ \forall i \in V,\ \forall r \in R \tag{2}$$

$$\sum_{i,j \in V \ \ i \neq j} \sum_{r \in R} t_{ij} x_{ijr}^k + \sum_{i \in V_0} \sum_{r \in R} \left(\frac{2 q_i t^u}{w^k} + t^p \right) y_{ir}^k \leq \ t_k \ \ \forall k \in K \tag{3}$$

$$t_k \leq t \leq T^{bef} \ \ \forall k \in K \tag{4}$$

$$\sum_{i,j \in V\ i \neq j} x_{ijr}^{k} t_{ij} + \sum_{i \in V_0} \left(\frac{2q_i t^u}{w^k} + t^p \right) y_{ir}^{k} \leq l^{max} \quad \forall k \in K, \forall r \in R \quad (5)$$

$$\sum_{i,j \in V\ i \neq j} \sum_{r \in R} \sum_{k \in K} x_{ijr}^{k} (e_{ij} m^f + t_{ij} w^k m^s) + \sum_{i \in V_0} (\frac{z_i q_i m^s}{100} +$$

$$2q_i t^u z_i m^s + t^p z_i m^s w^k) \leq b \quad (6)$$

$$b \leq B^{max} \quad (7)$$

$$\sum_{j \in V\ j \neq i} f_{jir}^{k} - f_{ijr}^{k} = q_i y_{ir}^{k} \quad \forall k \in K,\ \forall i \in V_0,\ \forall r \in R \quad (8)$$

$$q_j x_{0jr}^{k} \leq f_{0jr}^{k} \leq Q x_{0jr}^{k} \quad \forall k \in K,\ \forall j \in V\ i \neq j,\ \forall r \in R \quad (9)$$

$$f_{i0r}^{k} \leq (Q - q_i) x_{i0r}^{k} \quad \forall k \in K,\ \forall i \in V\ i \neq j,\ \forall r \in R \quad (10)$$

$$q_j x_{ijr}^{k} \leq f_{ijr}^{k} \leq (Q - q_i) x_{ijr}^{k} \quad \forall k \in K,\ \forall i,j \in V\ i \neq j,\ \forall r \in R \quad (11)$$

$$\sum_{k \in K} \sum_{r \in R} y_{ir}^{k} = z_i \quad \forall i \in V_0 \quad (12)$$

$$\sum_{i \in V(C)} q_i z_i + s_c \geq d_c \quad \forall c \in C \quad (13)$$

$$\sum_{i \in V(c)} u_{i,n-1} G z_i \leq \sum_{i \in V(c)} u_{in} z_i, \forall c \in C,\ \forall n \in N \backslash \{1\} \quad (14)$$

$$x_{ijr}^{k} \in \{0,1\} \quad \forall i,j \in V,\ \forall k \in K, \forall r \in R \quad (15)$$

$$f_{ijr}^{k} \geq 0 \quad \forall i,j \in V, \forall k \in K, \forall r \in R \quad (16)$$

$$y_{ir}^{k} \in \{0,1\} \quad \forall i \in V,\ \forall k \in K, \forall r \in R \quad (17)$$

$$z_i \in \{0,1\} \quad \forall i \in V_0 \quad (18)$$

$$t \geq 0 \quad (19)$$

$$t^k \geq 0 \quad \forall k \in \mathrm{K} \quad (20)$$

$$b \geq 0 \quad (21)$$

$$s_c \geq 0 \quad \forall c \in C \quad (22)$$

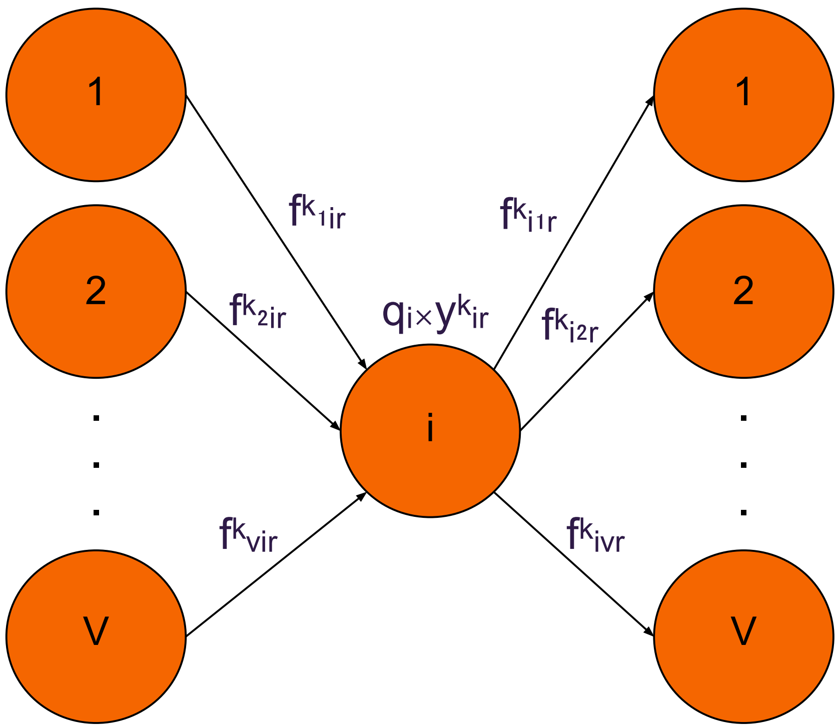
The objective function (1) is a multi-objective function with the primary purpose of minimizing the penalty cost of the logistics plan. The penalty cost is the SVI, multiplied by the demand shortage within each county, to prioritize commodity delivery under scarcity to the most vulnerable populations. The secondary objectives are to minimize financial cost and time consumed. This will allow for the conservation of financial resources and allow the SCEMD team to delay the start of the delivery process based on the time required by the delivery strategy (waiting to start delivery allows for more certainty in demand). Both time and financial cost have budgets that must be enforced, so their inclusion in the objective ensures that the most efficient logistics plan is chosen if there is a surplus.

Constraint (2) ensures the arrival at a destination cannot occur unless travel occurs to that node. The following three constraints relate to time. Constraint (3) limits the time each truck spends delivering, and constraint (4) ensures the total time is longer than the longest truck and shorter than the time budget. The next constraint (5) guarantees that each loop made by a truck consumes less time than an assumed shift length.

The amount of financial resources spent is constrained by constraints (6) and (7). Constraint (6) ensures the sum of the costs of delivery (gas and salary of workers on the vehicle) and the shelter opening costs (salary of emergency workers required per location to staff for three days) is smaller than the funds spent on the prepositioning strategy. Constraint (7) is the financial budget constraint and ensures the delivery strategy does not exceed the state's allocated budget for the disaster event.

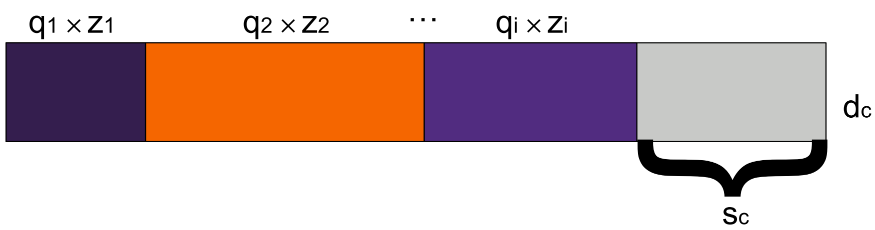
The following constraints regulate the flow within the network. Constraint (8) constrains the flow balance of commodities, as depicted in Figure 3.1. Constraints (9), (10), and (11) limit the flow capacity through the arcs. The next constraint (12) guarantees that each shelter is visited by one truck and that a truck arrives only if the shelter is open.

Figure 3.1: Commodity Flow Balance



The next constraint defines the demand shortage for each county. Constraint (13) forces the demand shortage to be more than the difference between the county's demand and the demand met within that county, as seen in Figure 3.2. Constraint (14) guarantees ordered opening of shelters based on the prioritization percentage (ensures 70% of shelters within a county and level open before any shelters of the next level within the county open) and the shelter's assigned priority level. The final constraints, (15) through (22), define the appropriate domains for each decision variable.

Figure 3.2: Demand Satisfaction and Shortage



Sensitivity Analysis

A sensitivity analysis was conducted to measure how variation in the inputs affects the solution to the model. The two inputs evaluated were the budget available, ranging from $100,000 to $350,000 in increments of $50,000, and the number of trucks available, ranging from four to seven in increments of one. Weights w^c=10^{-8} and w^t=10^{-4} where the cost and time scalars used in the objective to ensure the penalty cost is the primary objective and time and financial cost are secondary objectives. The sensitivity analysis results can be seen in Figure 3.3 and Table 3.3.

Figure 3.3: Results of Sensitivity Analysis

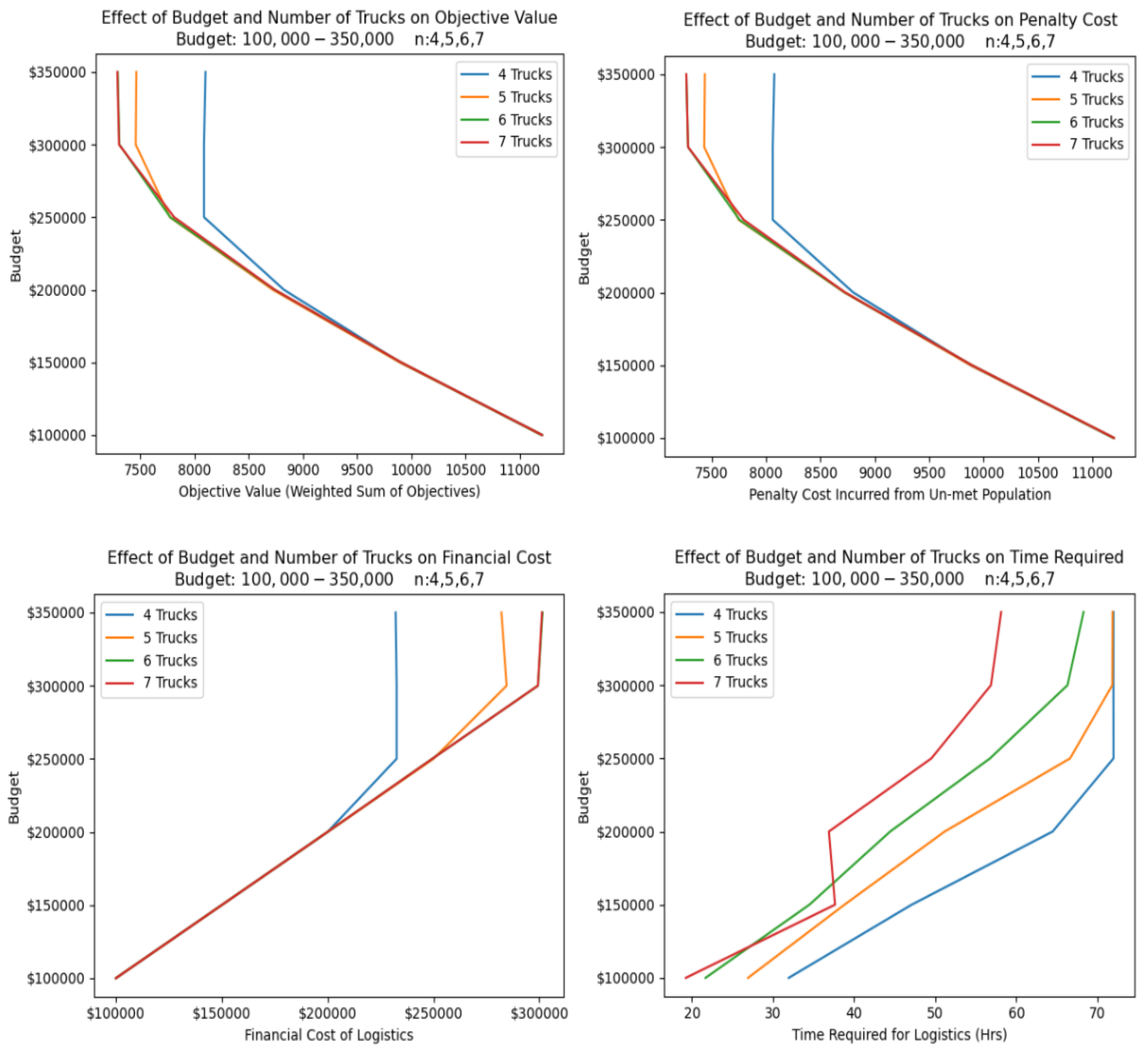


Table 3.3: Results of Sensitivity Analysis

Objective Value (OV)				
Max Budget (B_{max})	OV (nT=4)	OV (nT=5)	OV (nT=6)	OV (nT=7)
100,000	11,210.24	11,207.50	11,199.30	11,205.67
150,000	9,897.49	9,893.91	9,905.83	9,906.97
200,000	8,825.18	8,741.58	8,739.16	8,741.20
250,000	8,087.78	7,773.43	7,776.32	7,812.49
300,000	8,087.78	7,457.85	7,307.37	7,303.97
350,000	8,102.09	7,463.79	7,291.86	7,288.20

Penalty Cost (PC)				
Max Budget (B_{max})	PC (nT=4)	PC (nT=5)	PC (nT=6)	PC (nT=7)
100,000	11,198.75	11,197.81	11,191.50	11,198.75
150,000	9,880.53	9,879.94	9,893.42	9,893.42
200,000	8,801.97	8,723.16	8,723.16	8,727.91
250,000	8,061.86	7,749.44	7,755.89	7,794.66
300,000	8,061.86	7,431.98	7,283.49	7,283.49
350,000	8,076.18	7,437.92	7,267.27	7,267.27

Financial Cost ($b)				
Max Budget (B_{max})	b (nT=4)	b (nT=5)	b (nT=6)	b (nT=7)
100,000	$ 99,937.48	$ 99,949.20	$ 99,982.04	$ 99,995.03
150,000	$149,994.38	$149,998.34	$149,946.35	$149,971.02
200,000	$199,978.58	$199,998.26	$199,994.56	$199,949.54
250,000	$232,571.74	$249,971.73	$249,380.71	$249,449.20
300,000	$232,570.03	$284,565.99	$299,362.41	$299,305.91
350,000	$232,089.10	$282,080.58	$301,526.39	$301,261.11

Time Required (T hrs.)				
Max Budget (B_{max})	T (nT=4)	T (nT=5)	T (nT=6)	T (nT=7)
100,000	31.93	26.91	21.67	19.24
150,000	47.09	38.80	34.48	37.64
200,000	64.47	51.16	44.44	36.88
250,000	71.97	66.62	56.75	49.52
300,000	71.96	71.82	66.30	56.86
350,000	71.97	71.85	68.28	58.12

The results of the sensitivity analysis were analyzed based on how they affect four model outputs: objective value, total penalty cost, financial cost, and time required (each has its own graph in Figure 3.3 and its own sub-table in Table 3.3). All outputs followed the predicted trends. The objective value and penalty cost (upper left and upper right) are almost identical because penalty cost is the primary objective. These graphs (upper left and upper right) also reach limits when the penalty cost approaches 7267.2695 because the shelters have reached their maximum capacity in the counties with remaining demand. Approximately $300,000 is the limit for the financial cost (bottom left), indicating that as the penalty cost reaches its limit, the remaining budget is not utilized. Finally, the time required for the logistics plan (bottom right) reaches a limit of 72 hours, the maximum time possible before the event's landfall.

Ability to Meet Demand

Demand was met unevenly over the counties throughout the various budget levels and truck quantities used in the sensitivity analysis. To show how demand is met based on the SVI prioritization, two cases have been further visualized: four trucks with a $200,000 budget and six trucks with a $350,000 budget.

The first case was run with four trucks and a budget of $200,000 to depict a case where the penalty cost was not reduced to the minimum possible value based on the limitations of the scenario. In this scenario, Colleton, Dorchester, and Jasper's demand have been fulfilled fully because of the counties' high SVI values. Conversely, Charleston has the lowest SVI value, so it has one of the lowest percentages of demand fulfilled. Figure 3.4 shows a comparison between the percentage of demand fulfilled and the number of people with needs that are unsatisfied in this scenario for every county. A noticeable issue of fairness between counties can be seen in Figure 3.4; both Berkeley and Charleston County have similar demand shortages (5,876 vs. 6,540) but differing percentages of the population served (21% vs. 0%). This means Charleston's needy population is not being served because their county, as a whole, is less socially vulnerable.

In Figures 3.4 and 3.6, Horry County is seen as an outlier with a significantly higher quantity of demand than other counties because of the use of SVI in demand estimation (Horry has an average SVI and a larger population). Further investigation of the demand estimation to evaluate this high value's appropriateness is out of the scope of this research.

Figure 3.5 allows for a visualization of the logistics plan for this scenario. It depicts the starting location, the locations of shelters, truck routing, and shading indicating the proportion of demand fulfilled.

Figure 3.4: Comparison of Unserved Population Count and the Percentage of Population Served with Four Trucks and Budget of $200,000

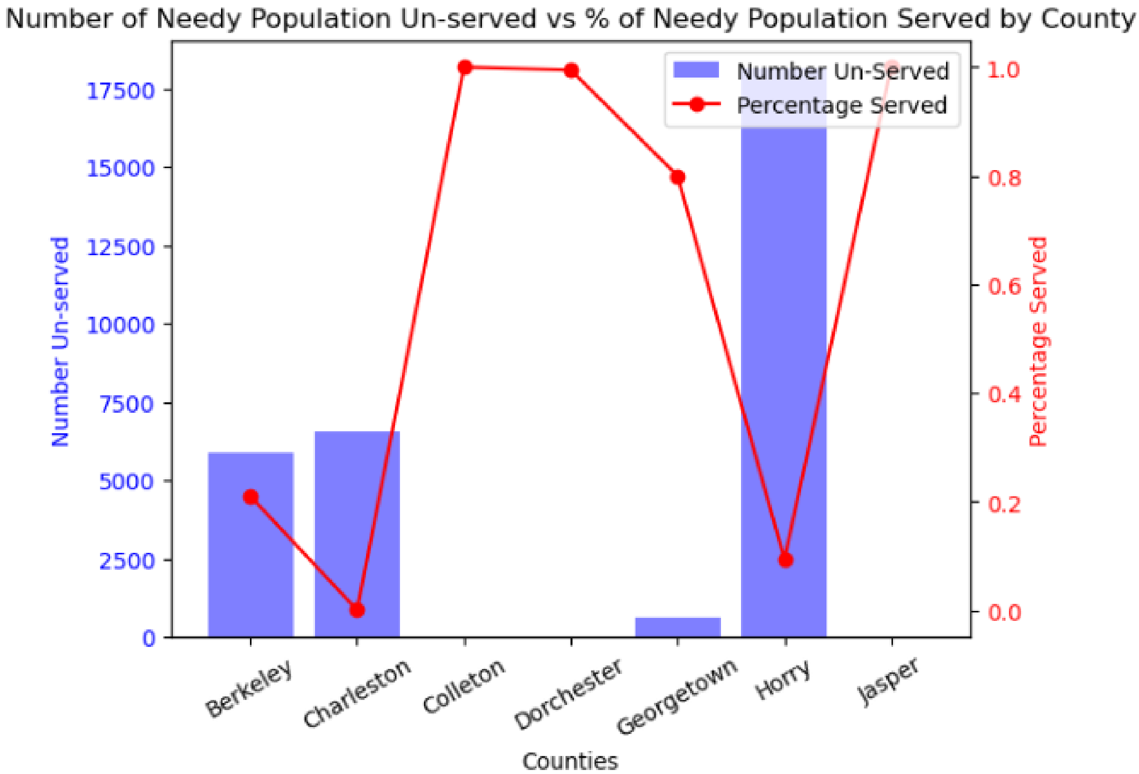
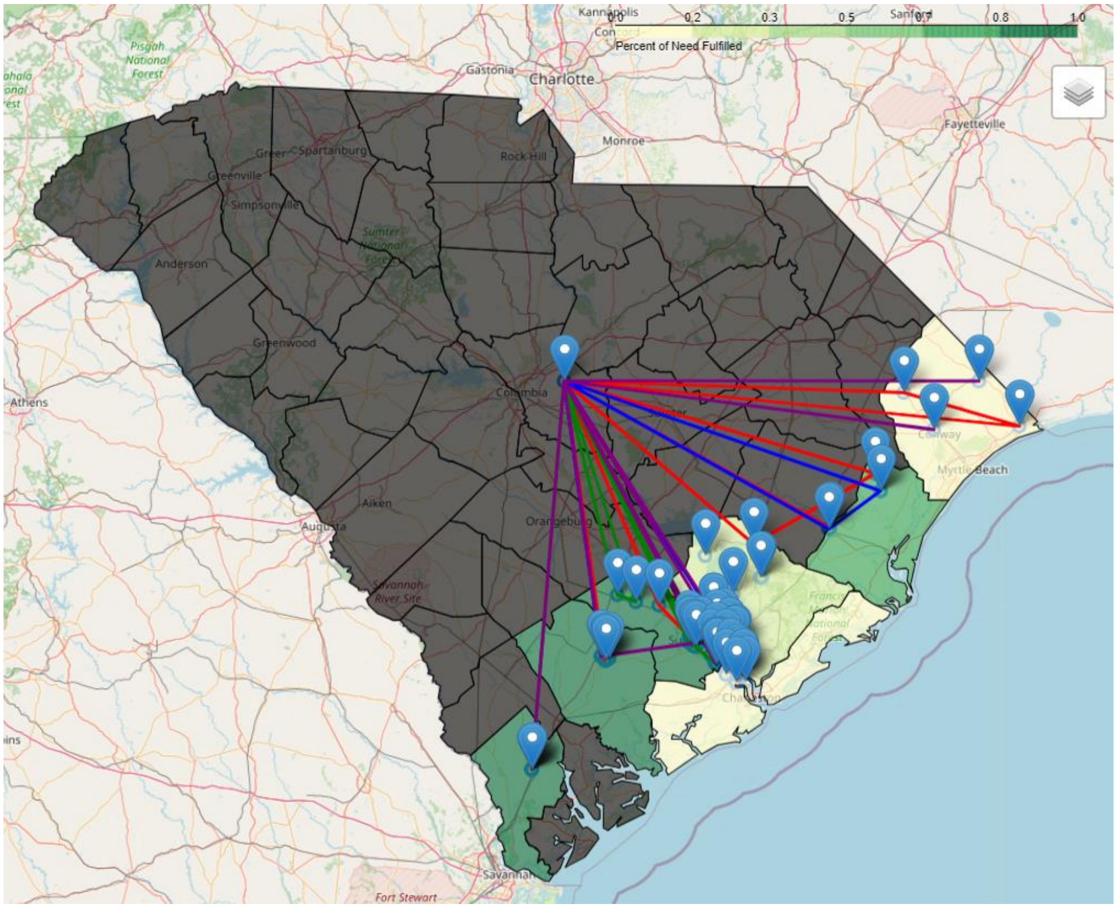


Table 3.4: Unserved Population Count and the Percentage of Population Served with Four Trucks and Budget of $200,000

County	Persons Un-Served	% of Needy Pop. Served
Berkeley	5876	21.01%
Charleston	6540	0.03%
Colleton	0	100.00%
Dorchester	36	99.50%
Georgetown	624	79.99%
Horry	18133	9.36%
Jasper	0	100.00%

Figure 3.5: Logistics Plan with Four Trucks and Budget of $200,000



The second case was run with six trucks and a budget of $350,000 to depict the case in this sensitivity analysis with the fewest number of trucks and lowest budget to achieve the lowest possible penalty cost. The lowest possible penalty cost value is 7267.2695 because, as previously discussed, the shelters have reached their maximum capacity in the counties with remaining demand. It can be seen in Figure 3.6 that all counties, excluding Horry, have unserved demand reduced below 2,000 people and have percentages of demand served above 70%. Again, Horry is an outlier due to how demand was calculated.

Figure 3.7 allows for a visualization of the logistics plan for this scenario and depicts the starting location, the locations of shelters, truck routing, and shading indicating the proportion of fulfilled demand. The shading in Figure 3.7 shows the drastic increase in demand able to be fulfilled compared to Figure 3.5. SCEMD has confirmed that their department's focus is fulfilling demand rather than achieving strict budget constraints, so the scenario depicted in Figures 3.6 and 3.7 more accurately represents the government's logic when considering the problem.

Figure 3.6: Comparison of Unserved Population Count and the Percentage of Population Served with Six Trucks and Budget of $350,000

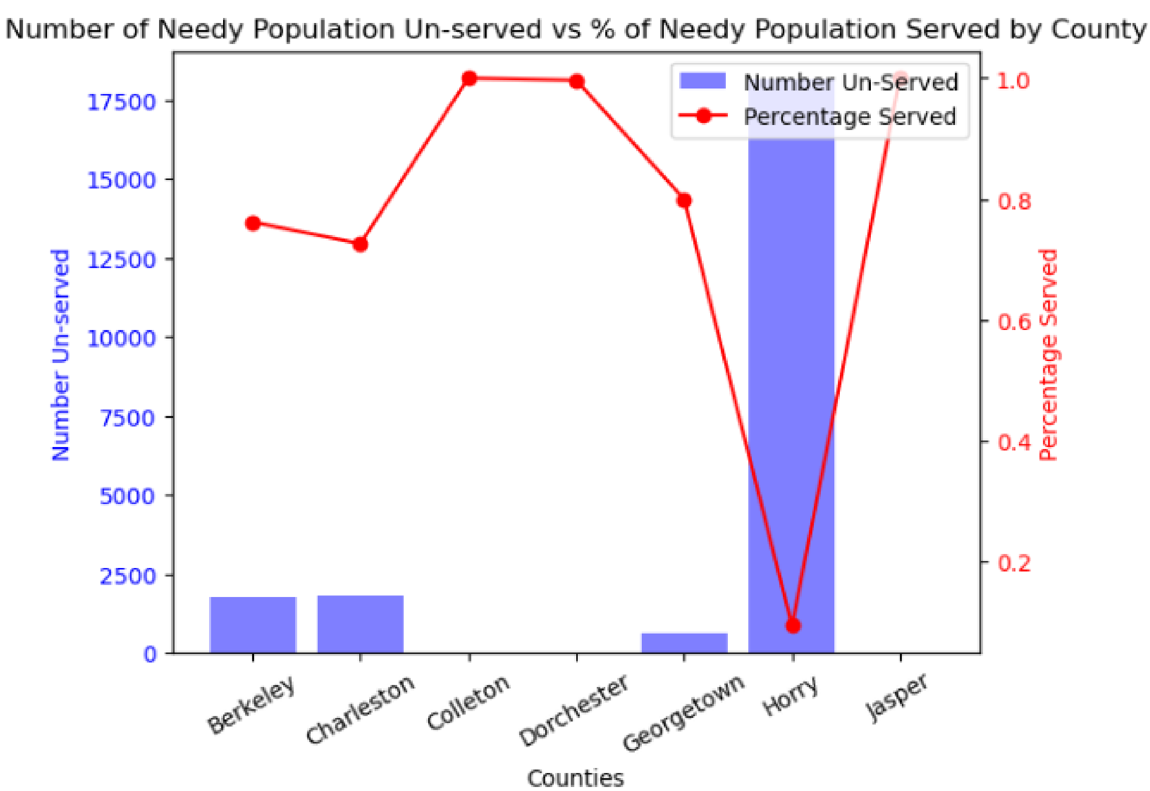
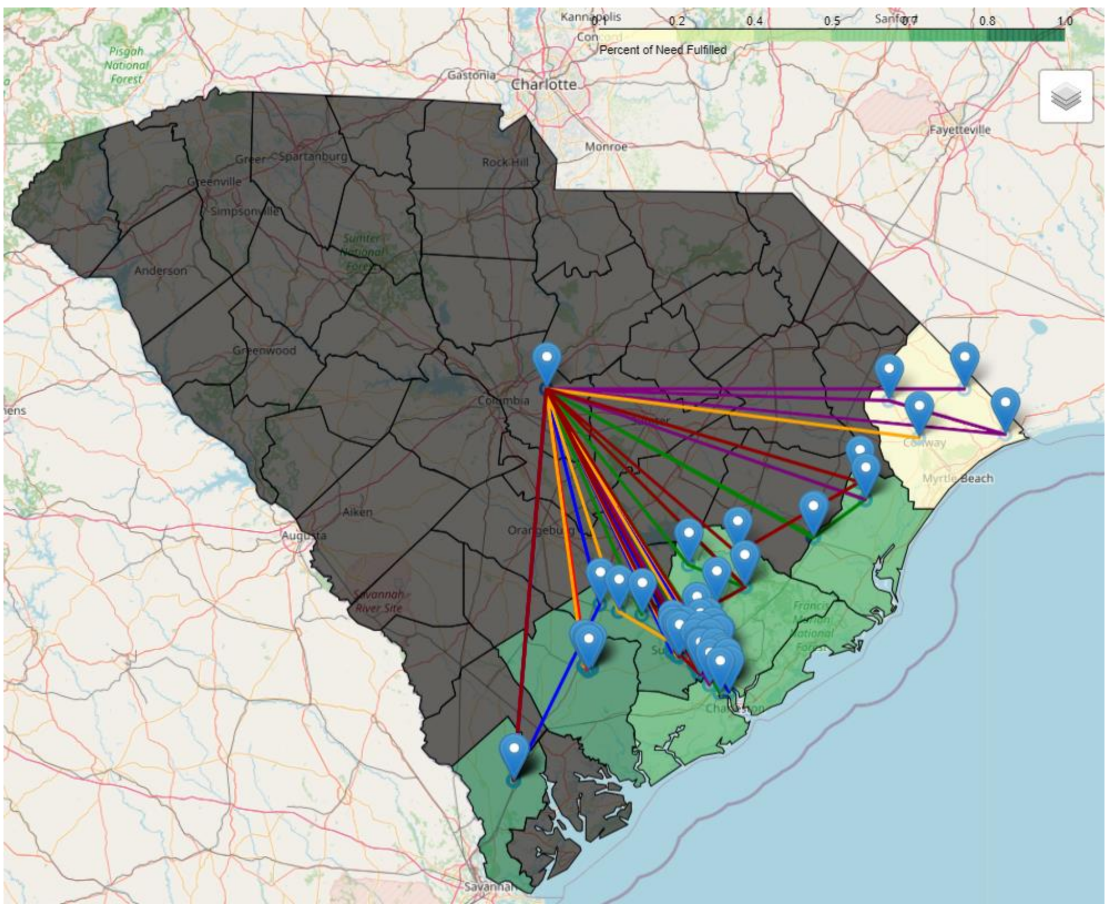


Table 3.5: Unserved Population Count and the Percentage of Population Served with Six Trucks and Budget of $350,000

County	Persons Un-Served	% of Needy Pop. Served
Berkeley	1771	76.19%
Charleston	1793	72.59%
Colleton	0	100.00%
Dorchester	23	99.67%
Georgetown	623	79.99%
Horry	18133	9.36%
Jasper	0	100.00%

Figure 3.7: Logistics Plan with Six Trucks and Budget of $350,000



Evaluation of Fairness

Figure 3.8 shows demand satisfaction through the percentage of demand fulfilled for the scenario where there are five trucks across the budget range of $100,000 to $350,000 with intervals of $25,000. Demand satisfaction occurs more rapidly in counties with high SVI, and in most scenarios, some counties have fully met demand before other counties receive any commodities. An example can be seen in Figure 3.8, where Colleton and Jasper have their demand fully met before Berkeley and Georgetown counties receive any kits. This is an issue of fairness because the objective is focused on maximizing the utility of the commodities.

In some cases, demand fulfilled for a county is higher at a lower budget level. In the example shown in Figure 3.8, Charleston has 58% of its demand fulfilled with the budget capped at $325,000, but when the budget increases to $350,000, the demand fulfilled is 49%. This is because some funds used to meet the demand at the lower budget level are redirected to meet demand in Horry County as the budget increases.

Figure 3.8: Percentage of Need Fulfilled with Five Trucks Over Budget Range

$100,000 to $350,000 with Intervals of $25,000

Map Interactivity and Solution Visualization

Interactive maps like Figures 3.5, 3.7, and 3.8 were made to allow decision-makers to visualize viable solutions further. Two types of maps were created to show static budget logistics and dynamic demand satisfaction. Both maps types function similarly to other maps users would be familiar with as it is intuitive to move and zoom.

Static Budget Visualizations

The Folium Python library was used for static budget visualization like Figures 3.5 and 3.7 [28]. It allows layers to be turned on and off to focus on relevant data. As seen in Figure 3.9, each truck has a layer, and the shading can also be turned off. Another feature of the interactive maps is that each node and arc can be selected and coded to contain pertinent information to the node or arc. In the example shown in Figure 3.10, the node marker contains the node's index and name.

Figure 3.9: Layers in Static Budget Map

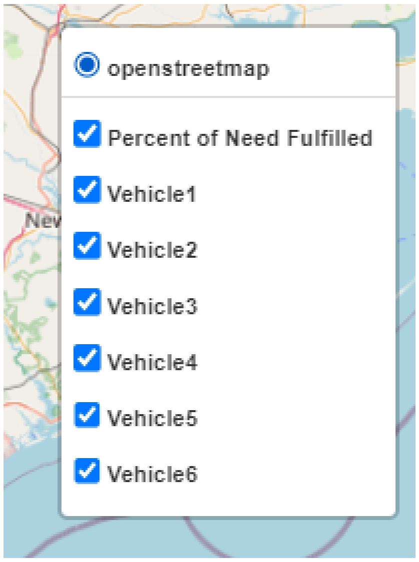
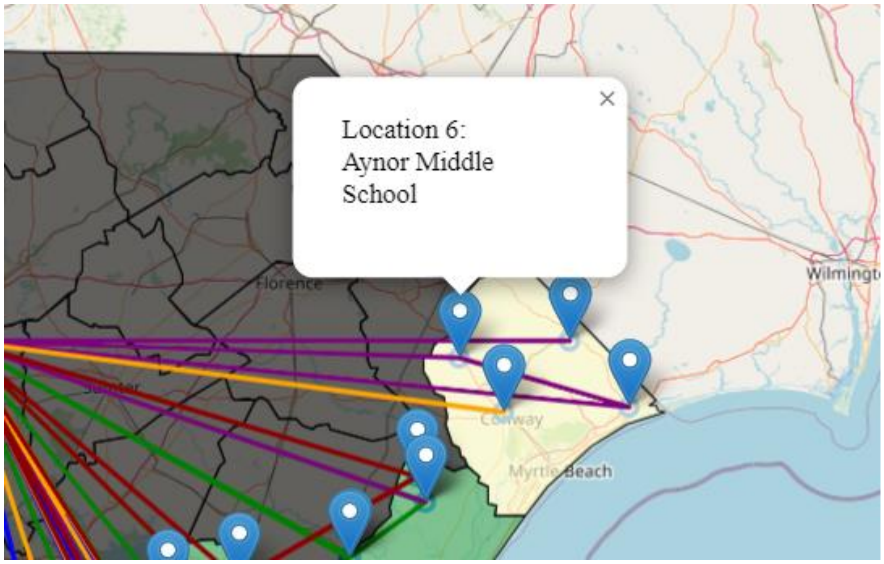


Figure 3.10: Node Labels in Static Budget Map



Dynamic Budget Visualization

The Plotly Python library was used for dynamic budget visualization like the example seen in Figure 3.8 [28]. It allows for a draggable sliding budget scale to evaluate various budget levels for a constant number of trucks, as visible in Figure 3.11. Also pictured in Figure 3.11 are the start and stop buttons, which allow the map to progress through budget levels automatically. Similarly to the static budget maps' node selection, the dynamic budget map allows county selection and provides the ability to code pertinent information into a popup. In the example pictured in Figure 3.12, the county marker contains the county's index, name, and the percent of demand fulfilled for the selected budget level.

Figure 3.11: Sliding Scale and Legend in Dynamic Budget Map

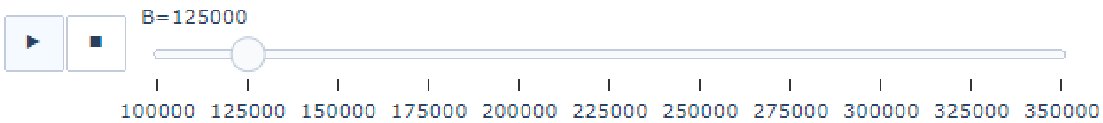
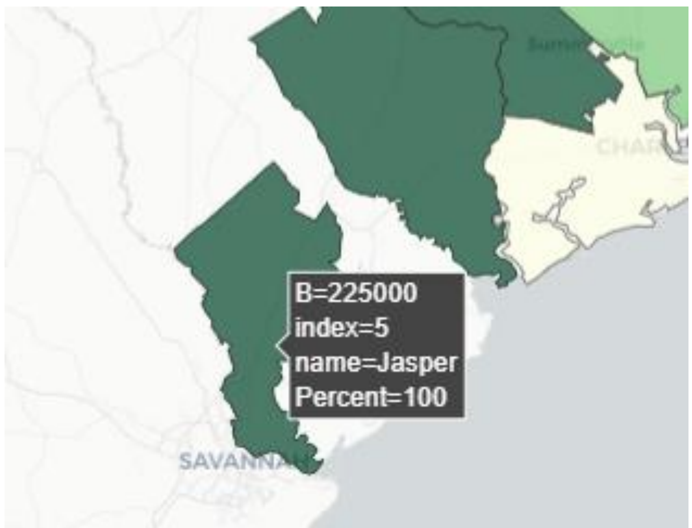


Figure 3.12: Node Labels in Dynamic Budget Map



CHAPTER FOUR

A TIME-EXPANDED NETWORK OPTIMIZATION MODEL FOR INTEGRATED PRE- AND POST-DISASTER LOGISTICS PLANNING

The multi-objective model described in this chapter is an extension of the pre-disaster sheltering model discussed in Chapter Three. The model's primary objective is to satisfy commodity demand as soon as possible, with the secondary objective of minimizing logistics costs. The model now accounts for two decisions, creating a pre-disaster and post-disaster strategy. It is beneficial for these decisions to be made in the same timeline rather than sequentially because it allows for the pre-positioning of PoD materials. Pre-positioning at PoD locations increases logistical efficiency and avoids post-landfall distribution when possible due to the potential for increased delivery costs (in terms of time and potential financial resources). The model is also indexed by time, allowing for scenario-specific supply chain disruptions and the introduction of staging areas and suppliers. These changes to the model increase the detail of operational-level decisions for the overarching tactical planning decisions, meaning the detailed operational-level decisions act as an optimization-based simulator. This model aims to assess differences between mixed load and single-commodity delivery, evaluate the decision maker's preference of objective prioritization, analyze fairness under scarcity, and identify bottlenecks in South Carolina's current logistics plan.

Hard Assumptions: Constraining the Model

Hard assumptions take the form of assumptions modeled through a constraint or are assumptions involved in the overall formulation of the model.

The first hard assumptions are related to when commodities and trucks become available at a node. It is assumed that commodities delivered become available upon the truck's arrival at a location, while the truck is not available until after a delay window designated for unloading, loading, and paperwork.

The next assumption is that a location's capacity is not considered in the model. This means that, in many cases, more individuals are arriving and receiving supplies at a shelter than the capacity of that shelter or cluster of shelters. Capacity is not considered in this model to reduce the number of constraints, thereby reducing the computational difficulty of the problem and allowing for short time periods to be considered.

It is also assumed that a perfect storm forecast is provided, and the decision to evacuate to a shelter by the affected population can be perfectly predicted, thereby allowing the model to be deterministic.

Timely satisfaction of demand is prioritized as the model distributes life-saving supplies. The minimized penalty cost is multiplied by each unit of unmet demand and summed for every hour to incentivize the satisfaction of demand as quickly as possible. Another demand assumption is that fraction satisfaction can occur as long as all commodities to achieve the fraction are included.

The financial cost is assumed to be the sum of the delivery cost and suppliers' commodity purchasing cost. The delivery cost is based on the fuel and personnel costs associated with the optimized logistics plan. Purchasing costs are based on the quantity of commodities in pallets that leave a supplier. In this model, the opening cost was not considered, as all locations included are considered "open."

Finally, the model assumes mixed commodity distribution, where there is no limit on the type of commodity in the truck, only on the space capacity within the truck. The model is adapted towards the end of this chapter, which includes the adjusted variable and constraints for single-commodity distribution.

Soft Assumptions: Data Collection and Formulation for Input

Clustering Shelter Nodes Using K-Means

The shelters in the Charleston area are close to one another, and the time to travel between them is too short to lead to a realistic time-expanded model, so the shelters were clustered. The clustering algorithm K-means was used because of its ability to cluster data by splitting the nodes into k groups and minimizing each cluster's sum of squares [29]. K was selected to be 20 (the starting warehouse was one of the clusters but was not paired with any other locations), and the result was 21 clusters of shelters because of the decision to separate the generated clusters based on the county boundaries due to demand being determined by county and not by shelter location. The reduction from 47 shelters to 21 clusters will also increase the efficiency of the model. A comparison between the nodes before and after clustering can be seen in Figures 4.1 and 4.2.

Figure 4.1: Nodes Before Clustering on Map

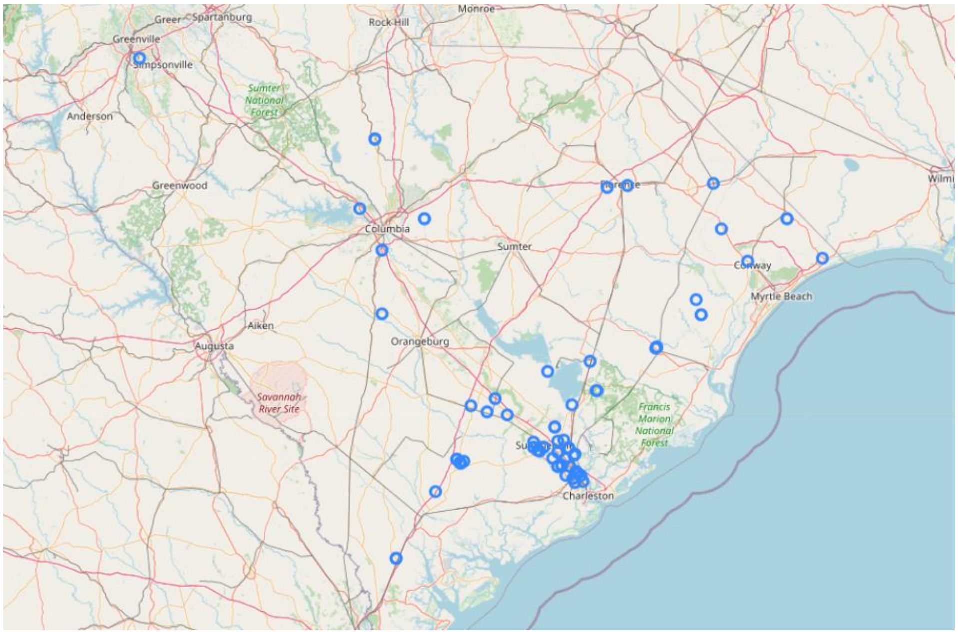
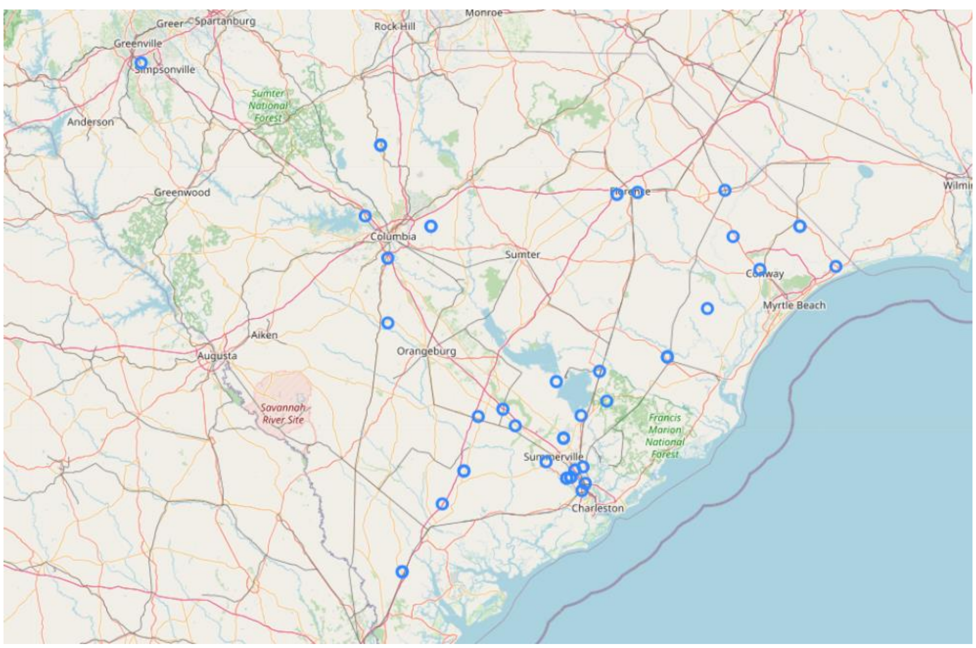


Figure 4.2: Clustered Nodes on Map



A representative location was selected as a shelter within the cluster because the truck would visit all locations regardless during the truck's delay period, making the shelter selected as the representative location insignificant. The capacities for all shelters in a cluster were summed, and this sum became the cluster's capacity. In this model, shelter groups relating to opening order are not considered due to the model's complexity and the inability to keep the integrity of the rankings when clustering.

Node Specific Data

The list of nodes is broken into four categories: suppliers/warehouses, clustered shelters, RSAs (regional staging areas or transshipment nodes), and PoDs. The supplier locations were provided by SCEMD and the warehouse locations were selected from Attachment 2 to the Cot Distribution Mission CONOP and Attachment A of the Logistics Plan in the South Carolina Emergency Operations Plan [2] [3]. The shelters were collected as described in Chapter 3 and clustered as discussed in the previous section. The RSA locations were taken from the SCEMP DMP 2023 Workbook. One PoD location was assumed for each county according to guidance from SCEMD; this location was selected as the shelter with the highest capacity. With the small size of the counties and the length of the time period considered, the exact location of a PoD within the county would not affect the solution.

Each node has relevant data which was collected or assumed that includes its geographical location (address, longitude, and latitude), capacity (for shelters only), the starting inventory of all commodities, the purchasing cost (for suppliers only), the starting quantity of trucks, the delay for trucks to load/unload, and the penalty cost (for PoDs and shelters only).

The geographical location is either listed in Annex H of the Hurricane Plan or was found using Google Maps. In some cases, when it came to suppliers and RSAs, an exact location could not be identified so an informed assumption was made. Shelter capacity is also found in Annex H, and for clustered shelters, the sum of individual shelter capacities is used as the cluster's capacity (capacity was used for data pre-processing, not in the model).

The SCEMD team communicated that they kept no perishable inventory in their warehouse, so the suppliers' starting inventory of food and water is an assumption based on the total commodities required to satisfy demand. There are two suppliers and the FEMA warehouse which could supply water. It is assumed that the starting location for half of the material required is the FEMA warehouse, while the two suppliers have a starting quantity of a quarter of the water required to meet demand. For food, there is one MRE supplier and the FEMA warehouse. It is assumed that one-third of the MREs come from the supplier and the other two-thirds of the food required to fulfill demand comes from the FEMA warehouse. The starting location and quantity of cots and blankets are taken from Attachment 2 to the Cot Distribution Mission [2]. The state has 12,000 cots, and according to the SCEMD, twice the quantity of blankets to accompany the cots. It is assumed for simplicity that all these cots are located at the McEntire Joint Base [2]

The purchasing cost from suppliers is assumed from averages of pallet prices taken from Amazon. The cost assumption for supplier water pallets is $361, which was calculated as an average of the price of the first ten results on Amazon. The assumption for the cost of MRE pallets to satisfy food demand is $1800, which was calculated as the average of the only four results on Amazon. Cots and blankets are borrowed from the Red Cross and not purchased, so their purchasing cost is $0 [2]. The cost assumption to supply from the FEMA Warehouse is assumed to be 150% of the cost from suppliers as FEMA is assumed to have a surcharge for counties to supply through them in exchange for commodities with a low lead time.

The starting location for all trucks is assumed to be the cot storage location at the McEntire Joint Base [2]. The assumption for truck quantity is 20, which was evaluated using a sensitivity analysis. The delay for trucks to load and unload is one time period for all locations that are not clustered, and for clustered locations, the delay was based on how many stops were required. If the cluster has two to three locations, two time periods are assumed to load/unload and if the cluster includes more than three locations, three time periods are assumed to load/unload.

Finally, the penalty cost is the SVI based on the county where the demand nodes are located. The same penalty cost is used for shelters and PoDs, and the values can be seen in Table 3.1 [26].

Scenario Generation Based on Hurricane Florence's Trajectory

The trajectory of Hurricane Florence, a 2018 storm making landfall in North Carolina, was the basis for the scenario used to generate demand. The windspeed was generated using HURREVAC's deterministic wind forecast at the time of landfall: 8 am on Friday, September 14th [30]. To increase the complexity of the required response, the level of the listed windspeed was raised by 35 mph to adjust each listed storm category by 2 (a Category 1 storm in HURREVAC became a Category 3 storm in the generated scenario, a strong tropical storm became a Category 2 storm, and a tropical storm became a Category 1 storm) [31]. Each county was assigned the highest hurricane category within its county lines. A map of windspeeds for Hurricane Florence can be seen in Figure 4.3 and the hurricane category levels for the counties relevant to this model's data set can be seen in Table 4.1.

Figure 4.3: Hurricane Florence Predicted Windspeed at Landfall [30]

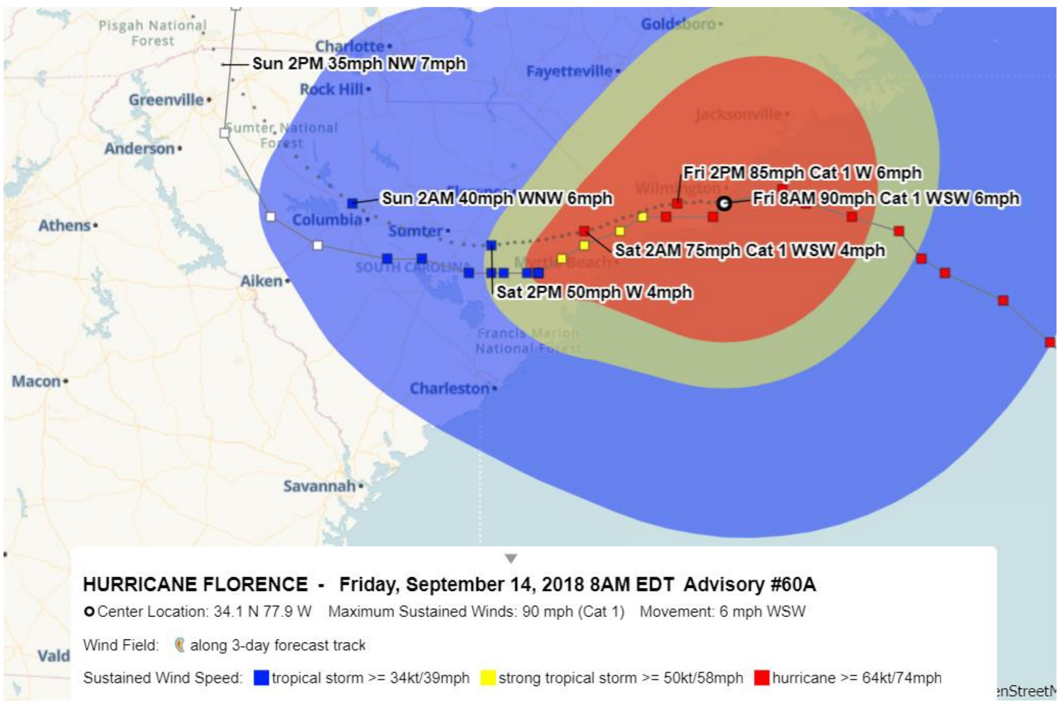


Table 4.1: Hurricane Category Level

County	Hurricane Category
Berkeley	Cat 2
Charleston	Cat 2
Colleton	Cat 1
Dorchester	Cat 1
Georgetown	Cat 3
Horry	Cat 3
Jasper	No Impact

Demand Calculation

The most intensive calculation required for each node was its demand calculation. The calculations used to calculate the worst-case deterministic demand for each county for a Category 3 storm can be seen in Equations 4.1 and 4.2. For more background on these calculations see the Chapter 3 section on Discrete Shelter Demand and Appendix A.

Equation 4.1: County Shelter Demand Calculation

$$D_c = I\ p_c\ E_{PS}\ E\ (1 + R)$$

where:
D_c: County demand for shelters
I: Total impacted persons [25]
p_c: SVI of county [26]
E_{PS}: Percentage of population likely to evacuate to a public shelter [27]
E: Percentage of population likely to evacuate [27]
R: Ratio of emergency workers (1/100)

Equation 4.2: County PoD Demand Calculation

$$D_{PoD} = I\ p_c\ (1 - E)$$

where:
D_{PoD}: County demand for shelters
I: Total impacted persons [25]
p_c: SVI of county [26]
E: Percentage of population likely to evacuate [27]

After Category 3 demand was found for both Shelters and PoDs, demand was translated into different hurricane category levels using the assumption that the number of persons needing basic commodities ($I \times p_c$) increases or decreases by 20% as the category moves away from Category 3 (persons needing basic commodities in a Category 1 storm is 20% less than Category 2, Category 2 is 20% less than Category 3, Category 3 is calculated using Equation 4.1 and 4.2, Category 4 is 20% more than Category 3, Category 5 is 20% more than Category 4). The demand values for the category level relevant to the current scenario, shown in Table 4.1, were used for the remaining calculations.

The demand of each county arrives over time (total time = T = 144 hrs), so the total demand for each county must be split over a distribution representing shelter arrival trends and pod pick-up arrival trends. Shelter arrival was distributed to time periods using an S-curve seen in Equation 4.3, and the curves for relevant counties can be seen in Figure 4.4 [32] [33]. PoD pick-up arrival was modeled using the assumption of a normal distribution where time post-disaster (T/2) was distributed into equal segments (quantity of segments = number of time periods in T/2) and then scaled to the size of the county's demand. This normal distribution assumes that most demand arrives at the middle of the time period and that PoD pick-up for commodities occurs once per disaster per person, meaning the area under the curve equals total demand as compared to if pick-up occurred once daily, as seen in Figure 4.5.

Equation 4.3: S-curve for Shelter Arrival

$$\frac{L}{1 + e^{-k(x-x_0)}}$$

where:
L: Total county demand for shelters to distribute
k: Steepness of curve (assumed 0.2)
x: Equally spaced points in time
x_0: Inflection point (assumed halfway through pre-positioning (T/4))

Figure 4.4: S-curve for Shelter Arrival

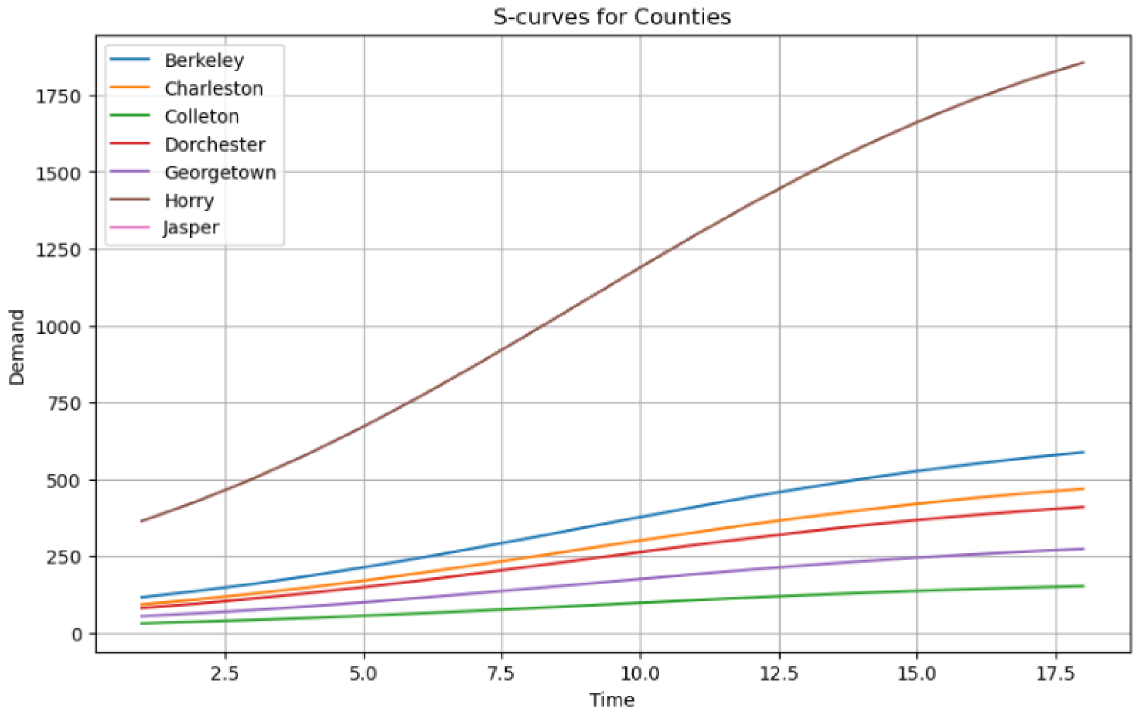
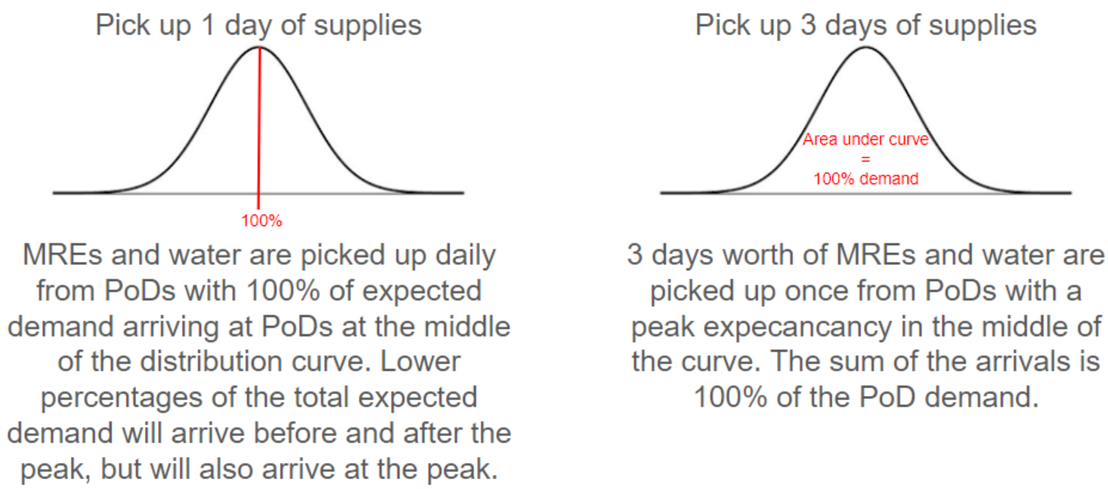


Figure 4.5: PoD Normal Distribution Modeling Options



The county demand per time period arriving at individual shelter clusters is proportional to the shelter's capacity in comparison to the total shelter capacity in that county. The calculation to find a cluster of shelters' demand can be seen in Equation 4.4.

A similar calculation was not required for PoD locations because there is only one PoD location per county, and all demand is assigned to that location.

Equation 4.4: Shelter's Capacity-based Demand

$$d_{it} = d_{ct} \frac{q_i}{\sum_{i \in V_1(c)} q_i} \forall i \in V_1 \; \forall t \in T$$

where:
V_1: Set of shelters
$V_1(c)$: Set of shelters in county $c \in C$
d_{it}: Shelter demand for shelter $i \in V_1$ per time period $t \in T^{Bef}$
d_{ct}: Total county demand for county $c \in C$ per time period $t \in T^{Bef}$
q_i: Shelter capacity in terms of pallets for shelter $i \in V_1$

Commodity Calculations

Demand for commodities in a shelter is considered for a three-day period due to the additional space necessary to meet requirements after three days, changing the sheltering scenario entirely [7]. According to the SCEMP DMP 2023 Workbook, an individual staying in a shelter requires three liters of water per day, two meals per day, two blankets, and one cot, so to fulfill the three-day demand, they must receive nine liters of water, six meals, two blankets, and one cot. All materials must be supplied to the individual before their demand can be considered met. From the logistics delivery standpoint, mixed commodity delivery is comparable to the kit delivery modeled in Chapter 3.

Demand for commodities at a PoD is again considered for three days after discussion with SCEMD officials. Water and meals are the only commodities in this model allocated at a PoD, as they are the most frequently and regularly required commodities distributed, according to SCEMD. To fulfill one unit of PoD demand, an individual must receive nine liters of water and six meals.

The number of pallet units per truck and commodities required to meet demand in fractional units of pallets can be seen in Table 4.2. The pallets per truck and average units per pallet were provided for the commodities in the SCEMD DMP 2023 Workbook. Factional units of pallets required to fulfill demand at the two types of demand nodes for each of the commodities seen in Table 4.2 were calculated using Equation 4.5.

Table 4.2: Demand Fulfillment and Vehicle Considerations per Commodity

Commodity	Pallet Units on Truck	Pieces per pallet	Fractional Pallet to meet Shelter Demand	Fractional Pallet to meet PoD Demand
Water	26	1008 L	0.008929	0.008929
Meals	48	576 MRE	0.010417	0.010417
Blankets	52	120 units	0.016667	0
Cots	52	48 units	0.020833	0

Equation 4.5: Fractional Pallet Units to Meet Demand

$$g_{ir} = \frac{1}{p_r/d_{ir}}$$

where:
g_{ir}: Fractional pallet unit of commodity r to fulfill demand for location type i
p_r: Pieces per pallet of commodity r (pieces units: water in L, meals in MRE, blankets in blankets, and cots in cots)
d_{ri}: Pieces of commodity r required for 3-day survival for location type i

Network Calculations

The distance and time between all nodes in the network were calculated using a Google Map API. The time values were converted to hours, then divided by the length of time in the time period, and rounded up as seen in Equation 4.6.

Equation 4.6: Travel Time

$$t_{ij} = \left\lceil \frac{\frac{T_{ij}}{3600}}{t^{period}} \right\rceil$$

where:
t_{ij}: Time required in time periods to travel link $(i,j) \in A$
t^{period}: Length in hours of time period
T_{ij}: Time required (seconds) to travel link $(i,j) \in A$

The cost to travel each link is based on the fuel cost to travel the distance as well as the salary of employees on the truck for the travel and delay time periods. It is assumed that four workers per truck were paid $15 per hour and that the fuel cost per mile was 10 cents. The calculation to determine the travel cost can be seen in Equation 4.7.

Equation 4.7: Travel Cost

$$m_{ij} = d_{ij}m_f + (t_{ij} + h_j)m_sW$$

where:
m_{ij}: Transportation cost of traveling link $(i,j) \in A$
d_{ij}: Distance in miles to travel link $(i,j) \in A$
t_{ij}: Time required in time periods to travel link $(i,j) \in A$
h_j: Truck delay in time periods at location j
W: Number of workers on truck
m_s: Salary cost per time period
m_f: Cost of fuel per mile

Defining the Network

In this model, warehouses and shelters act the same as discussed in the model described in Chapter 3. There are three additional types of nodes in this model: Points of Distribution, Regional Staging Areas, and Suppliers. Arcs will now span periods of time, and flow between all nodes will follow the theory of the time-expanded network for the minimum cost network flow problem.

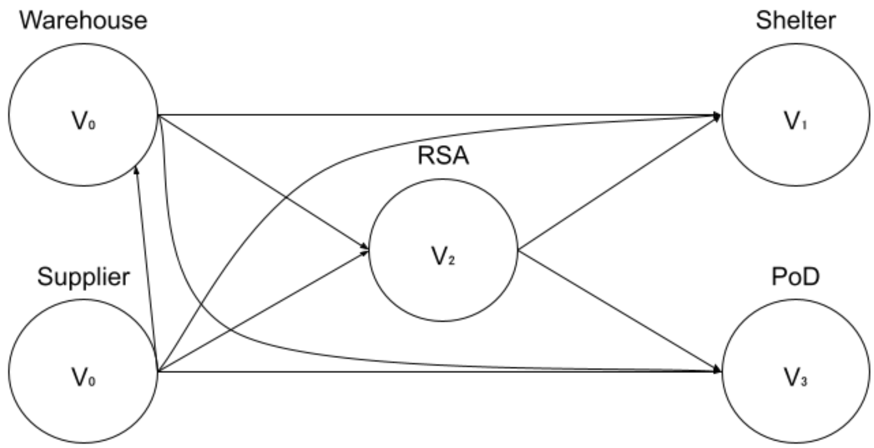
The post-disaster supply distribution occurs at nodes assigned as points of distribution (PoDs), each with a predicted demand. The PoDs distribute MREs and water to the stay-back population (affected individuals who chose not to evacuate). These supplies are considered lifesaving and must be delivered to prevent health crises [11].

Regional staging areas (RSAs) are another additional node type in this network. In the model, RSAs act as transshipment nodes.

The final type of new node is suppliers. The supplier nodes act similarly to the warehouses, but each has a cost associated with purchasing the commodity.

The arc set includes all links except those between PoDs and shelters, links that connect to PoDs and shelters with no demand, and links where $i = j$. Figure 4.6 depicts how material flows and the subsets of locations used in the model. Additionally, before and after the disaster's landfall, some arcs within the network may become unavailable in certain time periods for various reasons such as flooding, high winds, or evacuation traffic. In this scenario, it is assumed that no arcs become unavailable but the model is designed to accommodate this in a more complex scenario.

Figure 4.6: Commodity Distribution Flow and Location Subsets [3]



It takes a few days to establish a shelter, staging area, or PoD, and in this model, it is assumed that the opening process occurs prior to the start of commodity distribution.

Pre- and Post-Disaster Time-Expanded Network Model

This section introduces the pre- and post-disaster optimization model with a time-expanded network.

Sets:

V $i, j \in V$	Set of nodes
V_0	Subset of V including warehouses and suppliers
V_1	Subset of V including shelters
V_2	Subset of V including staging areas
V_3	Subset of V including PoDs
$(i, j) \in A$	Set of links from i to j ($i, j \in V$)
$r \in R$	Set of commodities
$t \in T$	Set of time periods
T^{bef}	Subset of time periods before landfall (Assumed 3 days)
T^{aft}	Subset of time periods after landfall (Assumed 3 days)

Parameters:

d_{it}	Demand at time $t \in T$ at location $i \in V_1, V_3$
N_{ir0}	Starting inventory of commodities $r \in R$ at location $i \in V$
C_{i0}	Starting number of trucks at location $i \in V$
p_i	Penalty cost of unfulfilled demand per location $i \in V_1, V_3$
t_{ijt}	Time periods to travel link $(i,j) \in A$ at departure time $t \in T$
h_i	Truck delay time at location $i \in V$
t^{period}	Time (in hours) in each time period
m_{ij}	Transportation cost of traveling link $(i,j) \in A$
w_r	Unit weight (capacity of truck taken) by commodity $r \in R$
w_b	Weight of financial cost in objective
c_{ir}	Unit procurement cost of commodity $r \in R$ from location $i \in V_0$
g_{ir}	Factor of demand per commodity $r \in R$ for location type $i \in V$

Decision Variables:

f_{ijrt}	Quantity of commodity $r \in R$ traveling link $(i,j) \in A$ starting at time period $t \in T$
I_{irt}	Inventory of commodity $r \in R$ at the start of time period $t \in T$ at node $i \in V$
J_{it}	Number of vehicles at location $i \in V$ at the start of time period $t \in T$
K_{ijt}	Number of vehicles traveling link $(i,j) \in A$ starting at time $t \in T$
U_{it}	Demand shortage at location $i \in V$ at time $t \in T$ (includes unsatisfied demand from previous time periods)
S_{it}	Demand satisfied at location $i \in V$ at time $t \in T$
b	Financial Resources delivery strategy requires to complete

Formulation:

$$min \sum_{i \in V} \sum_{t \in T} p_i U_{it}\, t^{period} + w_b \cdot b \quad (1)$$

s.t. $$U_{it} = U_{it-1} - S_{it} + d_{it} \;\; \forall i \in V \;\; \forall t \in T \backslash \{0\} \quad (2)$$

$$U_{i0} = d_{i0} \;\; \forall i \in V \quad (3)$$

$$S_{it} \le U_{it} \;\; \forall i \in V \;\; \forall t \in T \quad (4)$$

$$I_{irt+1} = I_{irt} - \sum_{j \in V:(i,j) \in A} f_{ijrt} + \sum_{j \in V:(i,j) \in A:\, t - t_{jit'} + 1 \ge 0} f_{jir,t-t_{jit'}+1} - S_{it} g_{ir} \;\; \forall i \in V \;\; \forall r \in R \;\; \forall t \in \{0,1, \ldots T-1\} \quad (5)$$

$$I_{ir0} = N_{ir0} \;\; \forall i \in V \;\; \forall r \in R \quad (6)$$

$$I_{irt} \ge \sum_{j \in V:(i,j) \in A} f_{ijrt} + S_{it} g_{ir} \;\; \forall i \in V \;\; \forall r \in R \;\; \forall t \in T \quad (7)$$

$$J_{it+1} = J_{it} - \sum_{j \in V:(i,j) \in A} K_{ijt} + \sum_{j \in V:(i,j) \in A:\, t - t_{jit'} + 1 - h_i \ge 0} K_{ji,t-t_{jit'}+1-h_i} \;\; \forall i \in V \;\; \forall t \in \{0,1, \ldots T-1\} \quad (8)$$

$$J_{i0} = C_{i0} \;\; \forall i \in V \quad (9)$$

$$J_{it} \ge \sum_{j \in V:(i,j) \in A} K_{ijt} \;\; \forall i \in V \;\; \forall t \in T \quad (10)$$

$$\sum_{i,j \in V:\,(i,j) \in A} \sum_{t \in T} m_{ij} K_{ijt} + \sum_{i \in V_0} \sum_{r \in R} c_{ir} (I_{ir0} - I_{irT}) \le b \quad (11)$$

$$\sum_{r \in R} w_r f_{ijrt} \le K_{ijt} \; \forall i,j \in V: (i,j) \in A \;\; \forall t \in T \quad (12)$$

$$f_{ijrt} \ge 0 \;\; \forall i,j \in V: (i,j) \in A \;\; \forall r \in R \;\; \forall t \in T \quad (13)$$

$$I_{irt} \ge 0 \;\; \forall i \in V \;\; \forall r \in R \;\; \forall t \in T \quad (14)$$

$$J_{it} \ge 0, integer \;\; \forall i \in V \;\; \forall t \in T \quad (15)$$

$$K_{ijt} \ge 0, integer \;\; \forall i,j \in V: (i,j) \in A \;\; \forall t \in T \quad (16)$$

$$U_{it} \ge 0 \;\; \forall i \in V \;\; \forall t \in T \quad (17)$$

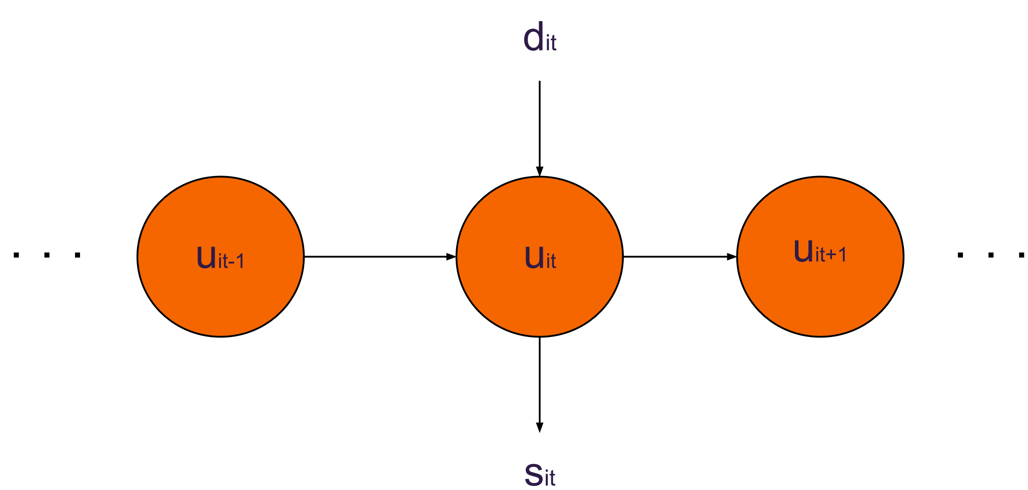
$$S_{it} \ge 0 \;\; \forall i \in V \;\; \forall t \in T \quad (18)$$

$$b \ge 0 \quad (19)$$

The objective function (1) is multi-objective, with the primary purpose of minimizing the penalty cost of the logistics plan by satisfying the demand for commodities as quickly as possible. The penalty cost is the SVI for the relevant county, multiplied by the time in each period to allow for the comparison of different lengths of periods and by the demand shortage at each location in every time period. This primary objective prioritizes commodity delivery to the most vulnerable populations. The secondary objective is to minimize financial costs, ensuring fiscal efficiency.

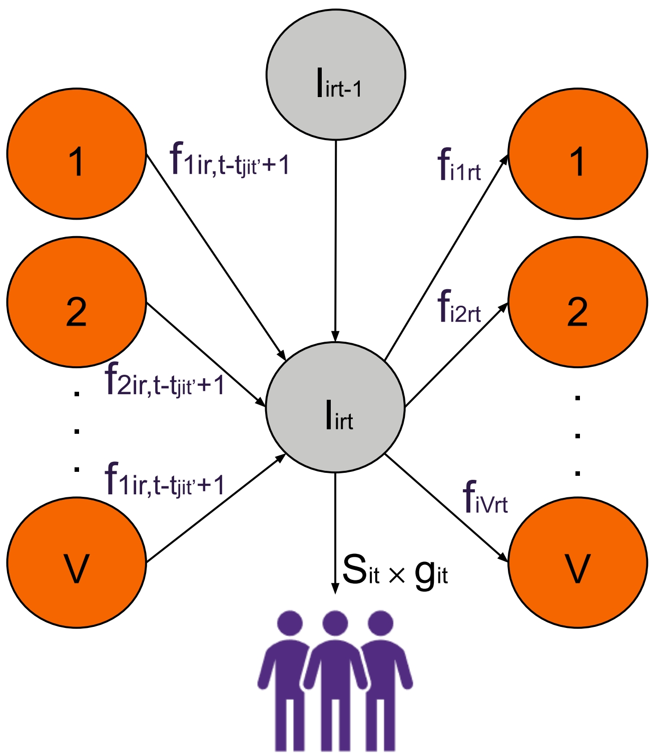
Constraints (2) through (4) regulate demand shortages and satisfaction. Constraint (2) defines the relationship between unmet demand, satisfied demand, and the demand of the current time period as seen in Figure 4.7. The next constraint (3) initializes the demand shortage. Constraint (4) guarantees that the demand satisfied is not greater than the unmet demand in the current time period.

Figure 4.7: Demand Flow Balance



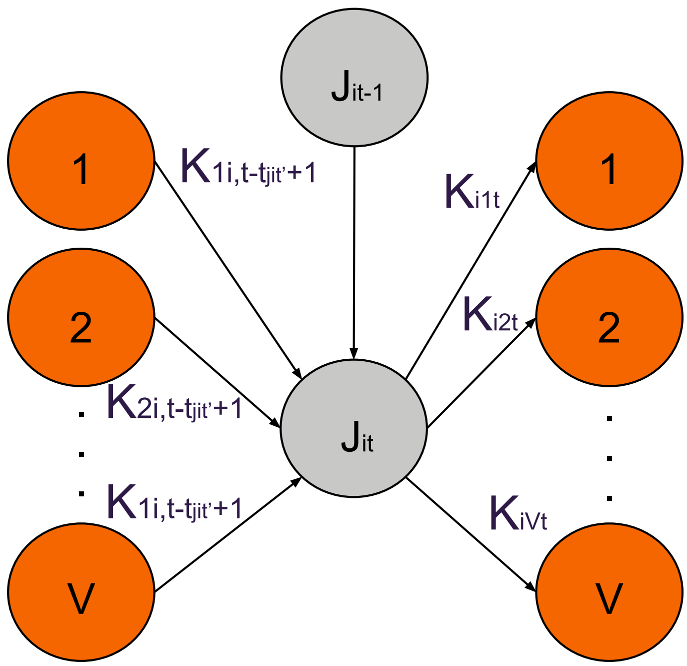
Constraints (5) through (7) constrain the flow of commodities in the network. Constraint (5) balances the flow of commodities while allowing commodities to leave the system as demand is met, which is depicted in Figure 4.8. The next constraint (6) provides the initial location of commodities in pallet quantities. Constraint (7) ensures the quantity of commodities leaving a location (to travel or to satisfy demand) in each time period is not greater than the current inventory.

Figure 4.8: Commodity Flow Balance



Constraints (8) through (10) constrain the flow of vehicles. Constraint (8) balances the flow of vehicles while accounting for the time to travel and the delay time required to complete paperwork as well as load and unload the truck. Figure 4.9 is a visualization of constraint (8). Constraint (9) provides the initial location of the trucks. The next constraint (10) guarantees the number of trucks leaving a node is not greater than the number currently located there.

Figure 4.9: Vehicle Flow Balance



Constraint (11) ensures the cost of the solution is less than the funds spent on the logistics plan. The cost is broken into two parts: travel and purchasing costs. The travel cost (m_{ij}) is based on the gas required to travel the distance from node i to j, the salary for employees to staff the vehicle for the time periods required for traveling the arc, and the delay to load and unload the vehicle. The purchasing cost is calculated based on the quantity of commodities leaving the suppliers and the commodity cost of each supplier.

The next constraint (12) guarantees that the truck capacity is not exceeded by limiting the number of pallets traveling an arc in each time period based on the number of trucks traveling that arc for each commodity. The final constraints (13) through (19) define the appropriate domains for each decision variable.

Adjusting for Single-Commodity Transit

The model was adjusted to allow only a singular commodity to be transported in a truck. The efficiency of mixed load and single-commodity distribution is compared later in this chapter. This affects the decision variable K_{ijt} which becomes K_{ijrt} and constraints (8), (10)-(12), and (16).

Adjusted Decision Variable:

K_{ijrt} Number of vehicles traveling $(i,j) \in A$ starting at time $t \in T$ carrying commodity $r \in R$

Adjusted Constraints:

$$J_{it+1} = J_{it} - \sum_{j \in V:(i,j) \in A} \sum_{r \in R} K_{ijrt} + \sum_{j \in V:(i,j) \in A:\, t-t_{jit'}+1-h_i \geq 0} \sum_{r \in R} K_{jir,t-t_{jit'}+1-h_i} \quad \forall i \in V \ \ \forall t \in \{0,1,\ldots T-1\} \tag{8}$$

$$J_{it} \geq \sum_{j \in V:(i,j) \in A} \sum_{r \in R} K_{ijrt} \quad \forall i \in V \ \ \forall t \in T \tag{10}$$

$$\sum_{i,j \in V:\,(i,j) \in A} \sum_{t \in T} \sum_{r \in R} m_{ij} K_{ijrt} + \sum_{i \in V_0} \sum_{r \in R} c_{ir}(I_{ir0} - I_{irT}) \leq b \tag{11}$$

$$w_r f_{ijrt} \leq K_{ijrt} \ \forall i,j \in V: (i,j) \in A \ \ \forall \mathrm{r} \in \mathrm{R} \ \ \forall t \in T \tag{12}$$

$$K_{ijrt} \geq 0, integer \ \ \forall i,j \in V: (i,j) \in A \ \ \forall r \in R \ \ \forall t \in T \tag{16}$$

Constraints (8), (10), (11), and (16) are structured the same as in the previous model; the only update is the change to variable K. In constraint (12), the left-hand side of the equation is no longer summed over set R and the constraint now applies to every commodity in set R, ensuring there is no mixing of commodities on trucks.

Analysis of Objective Weights

A decision maker's preference on the priority of minimizing penalty cost or financial cost impacts the solution. To evaluate the impact of a decision maker's prioritization, objective weights for the financial cost were analyzed, but first, an ideal time period must be determined.

Time Period Length Analysis

The problem was tested with a two- and four-hour time period for the case of 20 trucks to evaluate the ease and overall ability to find a solution (Table 4.3) (weight of financial cost used was w_b=1/100). The time period selected from this evaluation to be used in the following tests was four hours, as lengthening the time period drastically reduced the computational complexity of the problem.

Table 4.3: Time Period Length Analysis

Time Period	Objective	Penalty Cost	Financial Cost	% Gap From Lower Bound	Time to find Solution
2 hours	787812.20	763051.23	2476096.60	0.66%	9 hrs.
4 hours	873093.61	848142.60	2495101.04	0.03%	1 hr.

Analysis of Objective Weights

A trade-off curve of Pareto-optimal points was generated to test the weight of spending in the objective. SCEMD prefers to meet as much demand as possible, so the weight of the cost (w_b) of the logistics plan in the objective should allow for the cost to be minimized in a way that does not interfere with the primary objective of minimizing the socially vulnerable population's unmet demand. Weights smaller than 1/100 were found to have no significant effect on the objective and were not evaluated further. Various weights larger than 1/100 were evaluated to determine their effect on the primary and secondary objectives. The comparison between the primary and secondary objectives in a trade-off curve can be seen graphed in Figure 4.10 for various sampled weights. The total objective value, as well as all graphed values, can be seen in Table 4.4.

As seen in Figure 4.10, there is a drastic increase in penalty cost and a significant decrease in financial cost with values larger than w_b=1/4. This increased penalty cost shows a major shift in the priority balance between the two objectives.

SCEMD has indicated its primary priority is delivering life-saving supplies and that the cost of distribution is of much lower priority, meaning the government would favor a smaller weight, such as w_b=1/100 or w_b=1/10. Through this analysis, the weight of w_b=1/100 was found to be optimal for the scale of the model being considered, and this weight will be used throughout the subsequent tests.

Figure 4.10: Weights of Objectives for Mixed Load Distribution

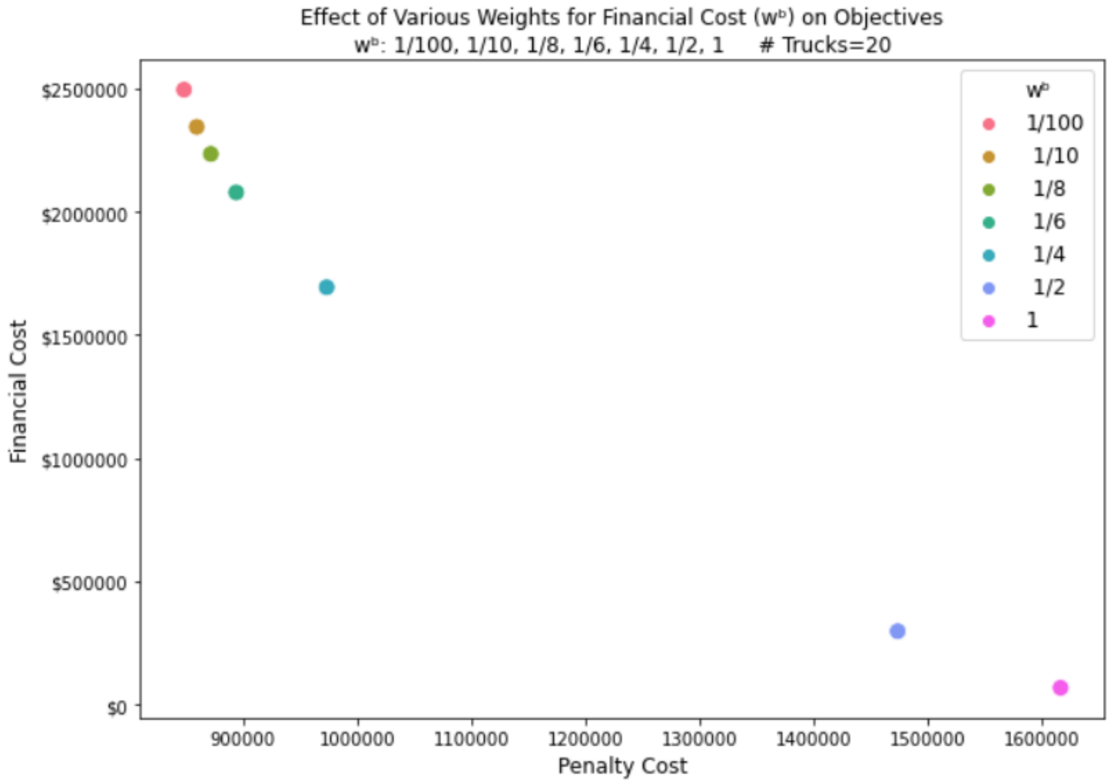


Table 4.4: Weights of Objectives for Mixed Load Distribution

Weight of Solution Cost (w_b)	Objective	Penalty Cost	Financial Cost
1/100	873,093.61	848,142.60	2,495,101.04
1/10	1,093,660.38	859,236.55	2,344,238.27
1/8	1,150,841.04	871,538.82	2,234,417.70
1/6	1,240,181.32	893,805.77	2,078,253.26
1/4	1,396,452.47	973,069.28	1,693,532.79
1/2	1,622,263.16	1,473,362.34	297,801.62
1	1,684,300.93	1,616,080.65	68,220.29

Comparing Mixed Load vs Single-Commodity Distribution

Two versions of the model, mixed load vs. single-commodity routing, were compared to determine optimality. Mixed load (kit-like delivery strategy) was thought to be a more efficient alternative, while single-commodity delivery is the current practice of SCEMD. This analysis will provide background on which routing strategy is most efficient and can be used to defend or adapt the current practice. In observing the optimal strategy, the sensitivity of both models has been tested with varying quantities of trucks.

As seen in Figure 4.11, there is the most separation between the objectives at the lowest truck quantities. It was determined that single-commodity delivery generally has a higher objective value and that as the number of trucks in the system increases, the objective value of single-commodity delivery approaches mixed load delivery (Figure 4.11).

Figure 4.11: Objective Values of Sensitivity Analysis with

Varying Truck Starting Quantities

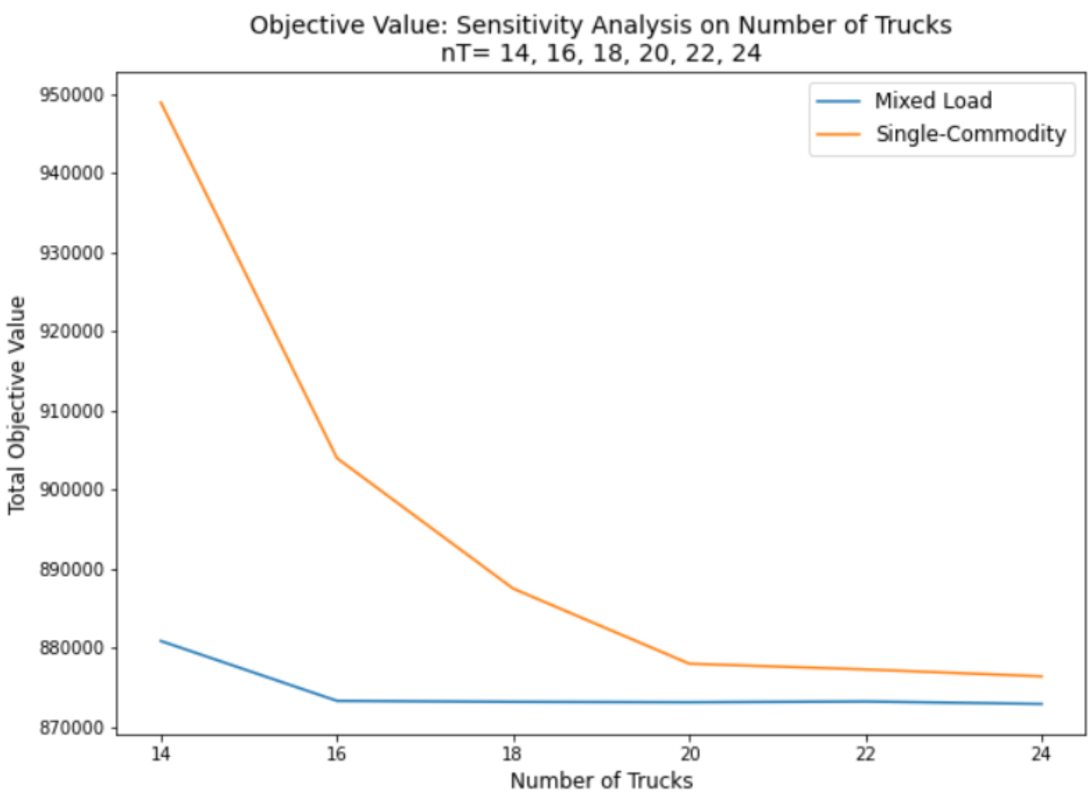


Table 4.5: Objective Value of Sensitivity Analysis with

Varying Truck Starting Quantities

Delivery Strategy	14	16	18	20	22	24
Mixed Load	880,841	873,271	873,150	873,094	873,190	872,881
Single-Commodity	948,929	903,955	887,466	877,968	877,244	876,366

Figure 4.12 shows the penalty cost values resulting from the sensitivity analysis, and the graph's shape is identical to that in Figure 4.11 due to the high priority of penalty cost in the objective (see Table 4.6 for data graphed). The financial cost of logistics is depicted in Figure 4.13, showing a significantly less clear trend, but as the number of trucks increases and the penalty cost decreases, the cost of delivery increases (see Table 4.7 for data graphed). The inconsistencies seen in the graph are due to the cost being the secondary objective. While the cost of single-commodity distribution appears more economical in Figure 4.13, less demand is met, so fewer commodities are being purchased from suppliers. This indicates that single-commodity distribution is not more affordable because, as shown in Figure 4.14, the ratio of purchasing cost to logistics cost is consistent across solutions. An aspect of logistics unaccounted for in these models is the cost of labor required for loading, unloading, and packaging materials, which would be more difficult with the mixed load strategy.

Figure 4.12: Penalty Cost of Sensitivity Analysis with Varying

Truck Starting Quantities

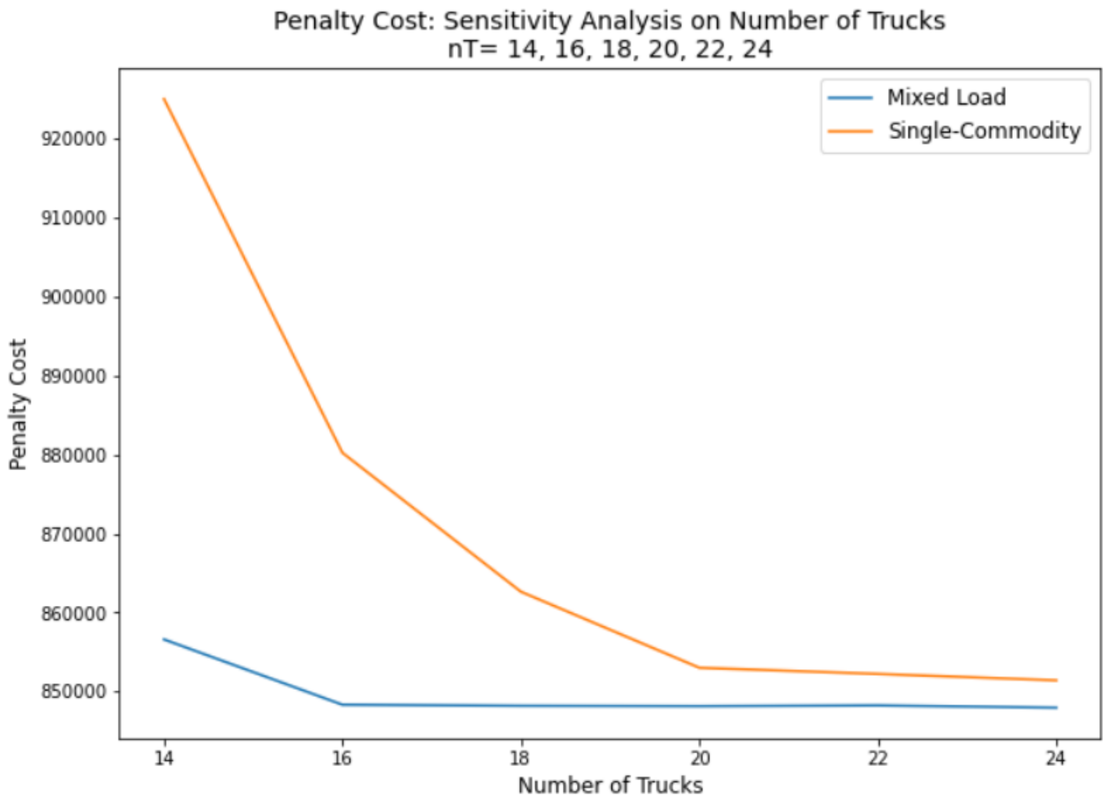


Table 4.6: Penalty Cost of Sensitivity Analysis with Varying Truck Starting Quantities

Delivery Strategy	14	16	18	20	22	24
Mixed Load	856,594	848,320	848,188	848,143	848,233	847,946
Single-Commodity	925,057	880,237	862,639	853,004	852,223	851,412

Figure 4.13: Logistics Cost of Sensitivity Analysis with Varying

Truck Starting Quantities

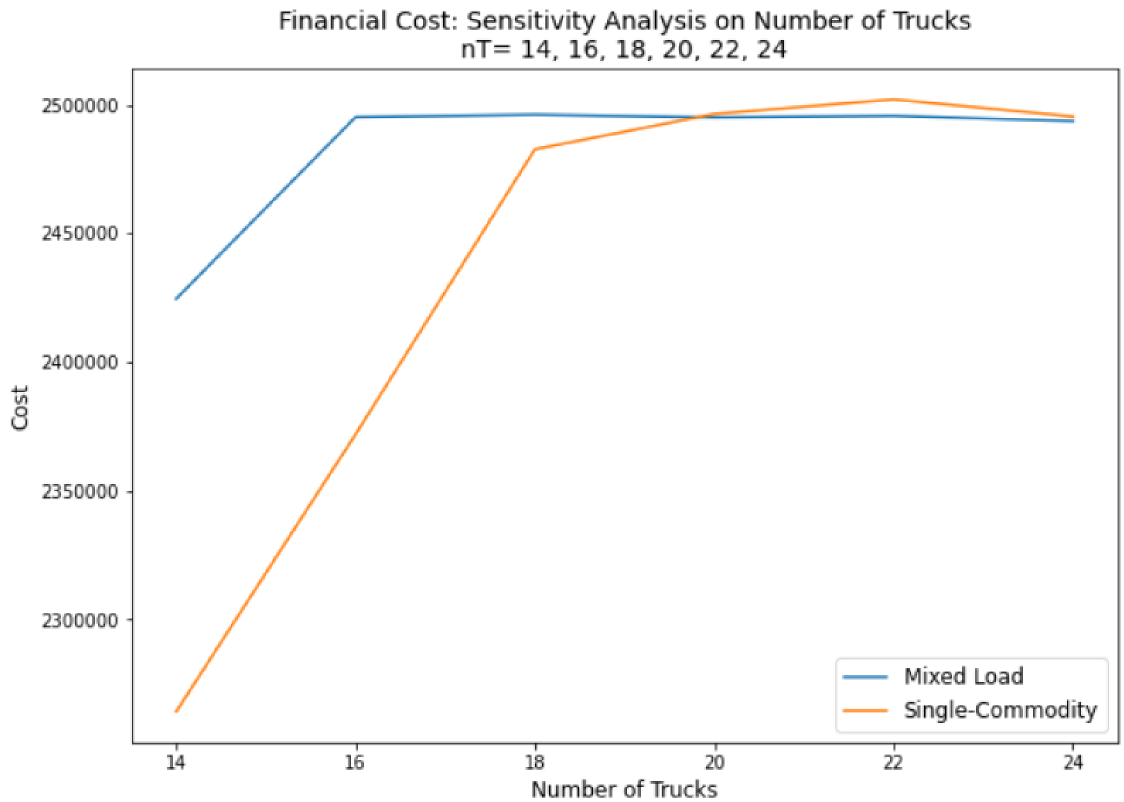
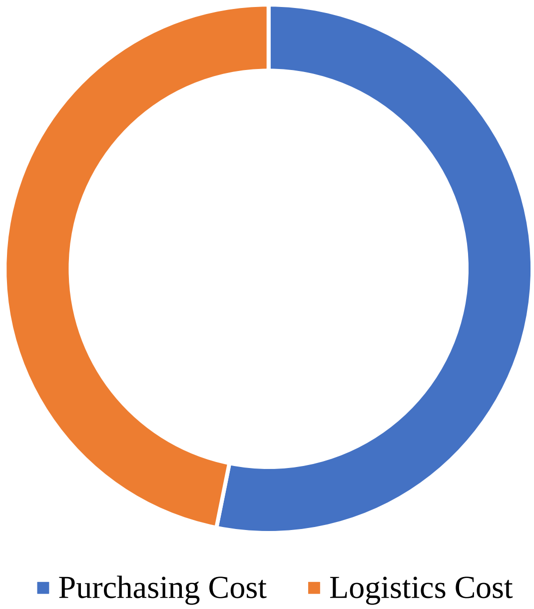


Table 4.7: Logistics Cost of Sensitivity Analysis with Varying Truck Starting Quantities

Delivery Strat.	14	16	18	20	22	24
Mixed Load	2,424,649	2,495,217	2,496,128	2,495,101	2,495,711	2,493,598
Single-Comm.	2,264,247	2,371,963	2,482,688	2,496,381	2,502,046	2,495,404

Figure 4.14: Ratio of Financial Cost Parts



The conclusion from Figures 4.11, 4.12, and 4.13 is that mixed delivery is more effective for disaster logistics planning in South Carolina with the given inputs.

In the tests conducted so far, the penalty cost has approached a high value (see Figure 4.12), meaning there is a limiting factor preventing the solution from further reducing the penalty cost. This factor is not the number of trucks, as increasing the vehicle quantity does not drastically affect the penalty cost. For this model, the starting quantities of cots and blankets are considered the limiting factor in further reducing unmet demand. The number of cots used as an input was based on actual data rather than a quantity which would allow for all the demand to be met [2]. In the next sections, a case will be considered where there are enough cots to meet demand.

Analysis of Objective Weights with No Cot Limitations

The input values for the starting quantities at suppliers and warehouses must be adjusted to consider a model where all demand could be met. Table 4.8 shows the minimum quantity that could be used to meet demand with a limited number of cots and the actual model input in the first two columns (the true quantity used is slightly higher to ensure all demand has the chance to be satisfied). The final two columns in Table 4.8 show the minimum quantity which could be used to meet demand with an "unlimited" supply of cots and the value used as an input for the model.

Table 4.8: Starting Quantities (in Pallets) of Commodities in the Model

Commodity	Min. Quantity	Model Input	Min. Quantity with no Cot Lim.	Model Input with no Cot Lim.
Water	768	778	1019	1024
Meals	896	907	1189	1194
Blankets	-	250	850	855
Cots	-	200	680	684

The objectives' weights were measured again to determine the optimal weight of financial cost in the objective function; the trade-off curve and results can be seen in Figure 4.15 and Table 4.9. Figure 4.15 resembles Figure 4.10, so the same conclusions were drawn, and w_b=1/100 will again be the weight used throughout the subsequent tests.

Figure 4.15: Weights of Objectives with No Cot Limitation for Mixed Load Distribution

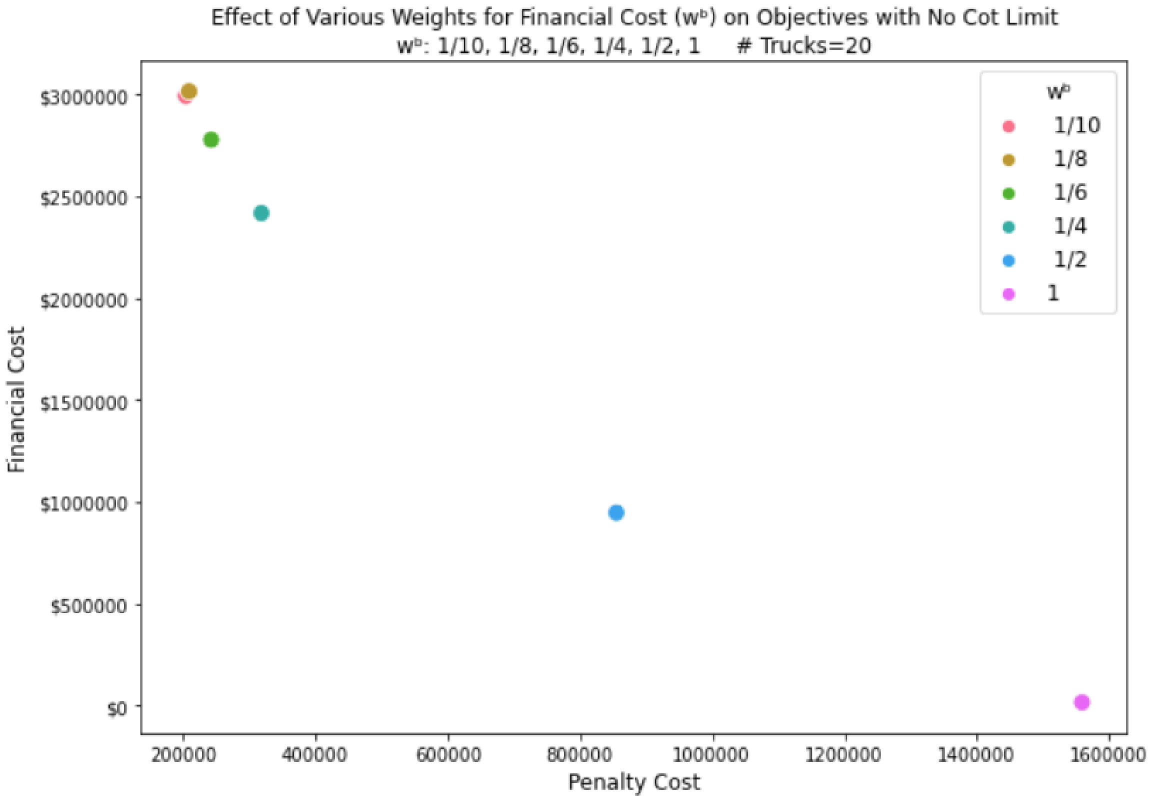


Table 4.9: Weights of Objectives with No Cot Limitations for Mixed Load Distribution

Weight of Solution Cost (w_b)	Objective	Penalty Cost	Financial Cost
1/10	503,423.72	204,253.45	2,991,702.62
1/8	585,981.89	209,273.14	3,013,670.06
1/6	705,335.13	242,629.62	2,776,233.06
1/4	922,535.58	318,560.51	2,415,900.29
1/2	1,328,173.44	855,198.54	945,948.81
1	1,573,934.60	1,558,899.16	15,035.43

Comparing Mixed vs Single-Commodity Distribution with No Cot Limitations

The sensitivity of the quantity of trucks was re-evaluated under the condition that there were enough cots to fulfill all demand; the graph and table of objective values can be seen in Figure 4.16 and Table 4.10. This trend is much more dramatic, indicating that additional cots in the starting value allows the number of trucks to become the bottleneck. Truck quantities were not tested beyond 20 because, at this point, practically all demand is satisfied.

Figure 4.16 shows that mixed load and single-commodity distribution strategies follow parallel curves rather than converging curves, as seen in the scenarios with limited cots. This is because there is no longer a limit on the ability to meet demand. Figures 4.16 and 4.17 show that the mixed load strategy is again more efficient at fulfilling demand with a limited number of trucks.

Figure 4.16: Objective Values of Sensitivity Analysis with Varying Truck Starting Quantities and No Cot Limitations

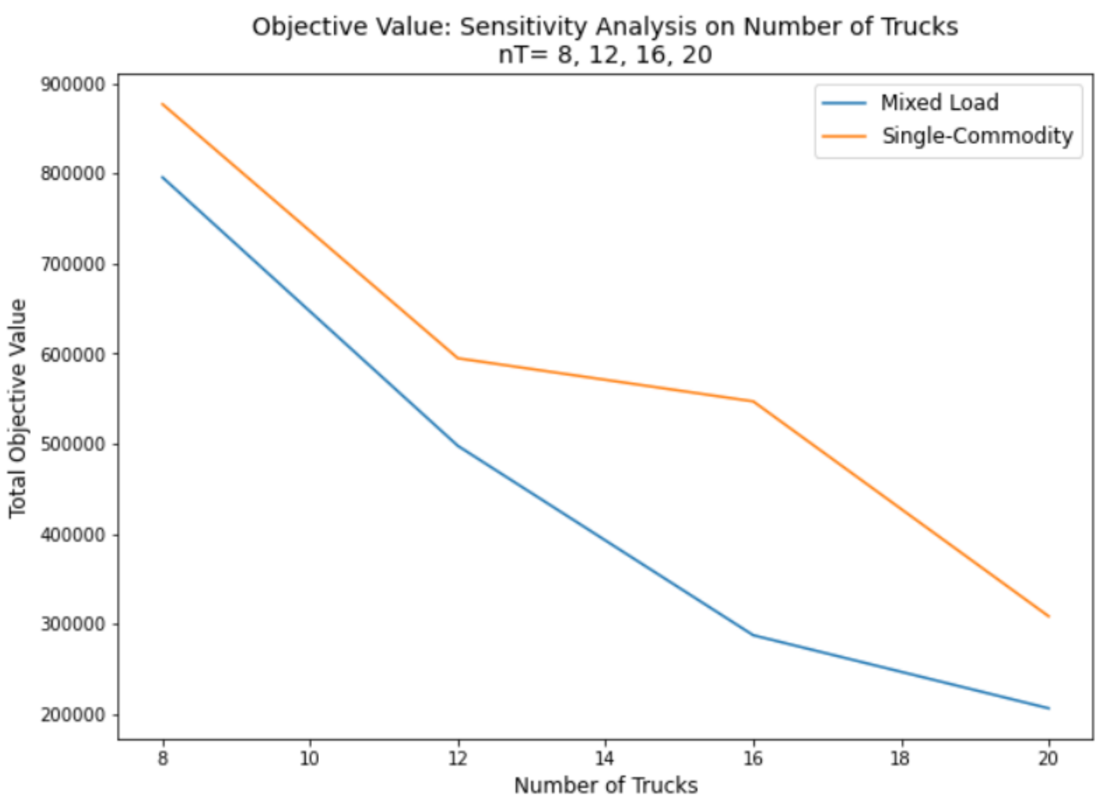


Table 4.10: Objective Value of Sensitivity Analysis with Varying Truck Starting Quantities and No Cot Limitations

Delivery Strategy	8 Trucks	12 Trucks	16 Trucks	20 Trucks
Mixed Load	795,866.9	497,599.1	287,265.2	206,079.8
Single-Commodity	877,149.8	594,881.8	546,994.7	308,294.9

Figure 4.17 depicts the penalty cost values from the sensitivity analysis. The graph's shape is practically identical to that in Figure 4.16 because penalty cost has a high priority in the objective (see Table 4.11 for data graphed). The financial cost of logistics is shown in Figure 4.18. As the number of trucks increases and the penalty cost decreases, the cost of delivery increases (see Table 4.12 for the graphed data).

Figure 4.17: Penalty Cost of Sensitivity Analysis with Varying Truck Starting Quantities and No Cot Limitations

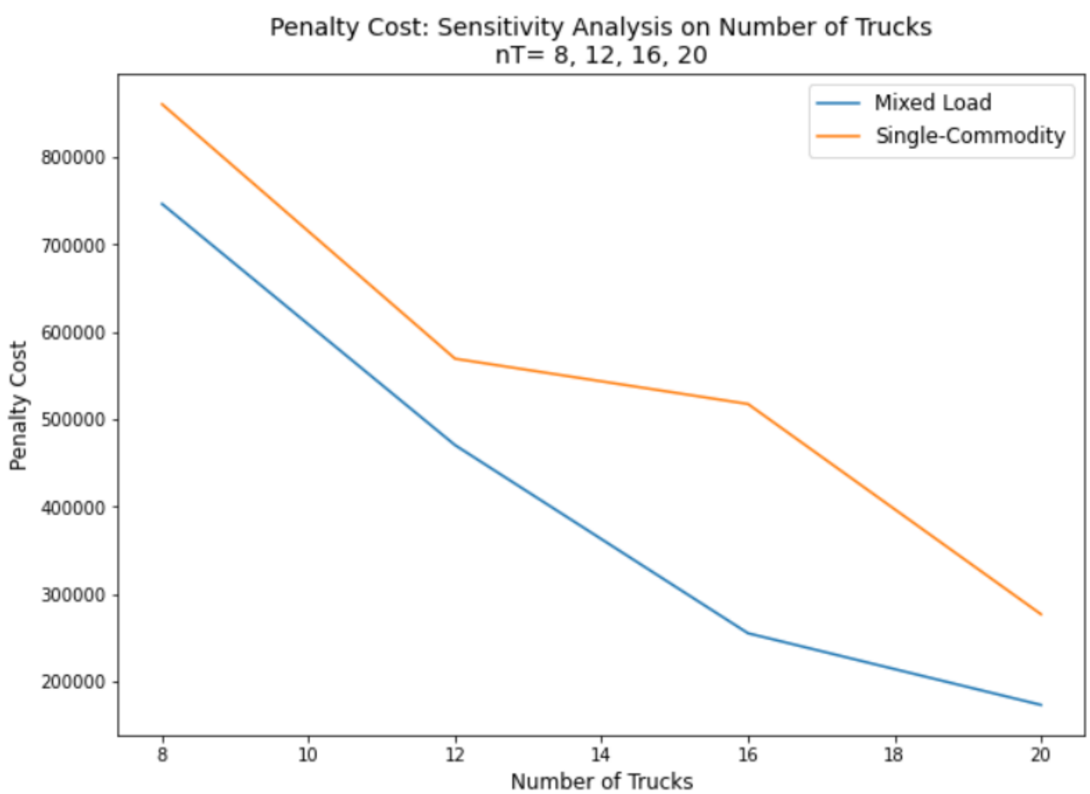


Table 4.11: Penalty Cost of Sensitivity Analysis with Varying Truck

Starting Quantities and No Cot Limitations

Delivery Strategy	8 Trucks	12 Trucks	16 Trucks	20 Trucks
Mixed Load	746,491.3	470,558.5	255,328.8	173,356.2
Single-Commodity	860,537.5	569,402.3	517,592.2	277,078.6

Figure 4.18: Logistics Cost of Sensitivity Analysis with Varying Truck

Starting Quantities and No Cot Limitations

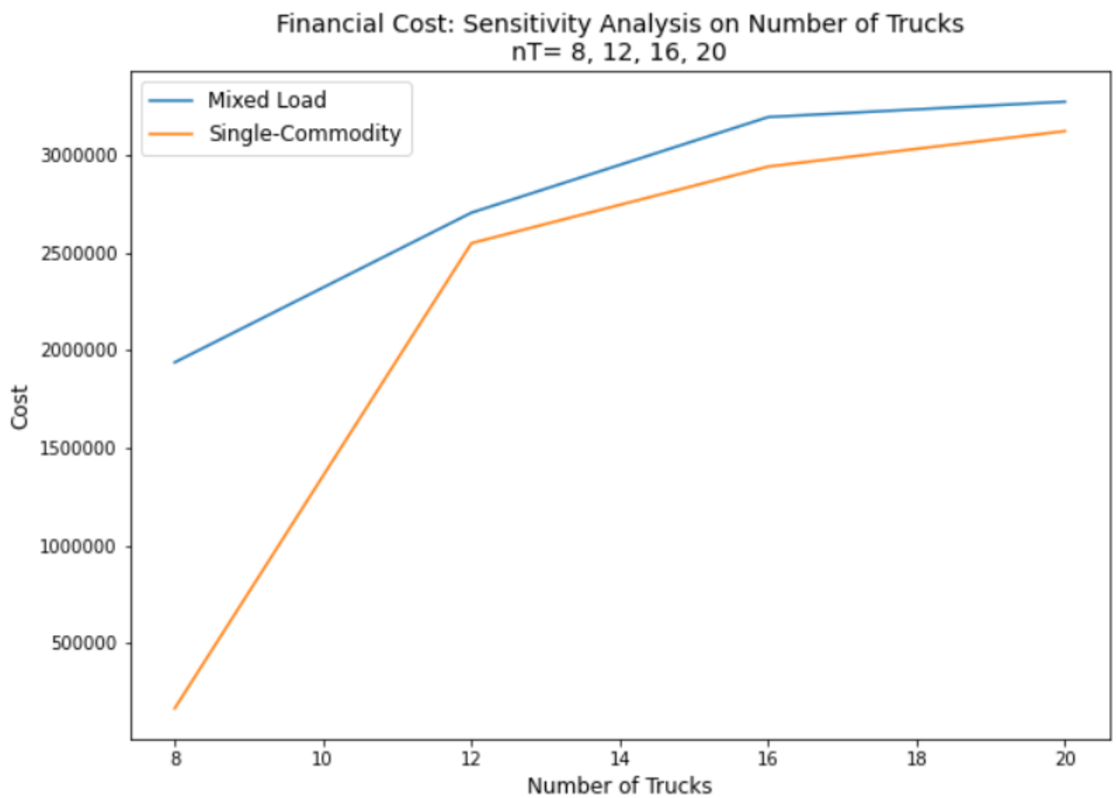


Table 4.12: Logistics Cost of Sensitivity Analysis with Varying Truck

Starting Quantities and No Cot Limitations

Delivery Strategy	8 Trucks	12 Trucks	16 Trucks	20 Trucks
Mixed Load	1,937,560	2,704,066	3,193,639	3,272,360
Single-Commodity	166,128	2,547,952	2,940,242	3,121,627

The solution to the model, when it has all the cots and blankets required to meet demand, has a large gap from the lower bound. The gaps can be seen in Table 4.13. This analysis has been based on the best solution found, but the best solution could be lower because of the gap. The gap does not influence the trends identified in this section but does affect the specific data values listed in Tables 4.10, 4.11, and 4.12.

Table 4.13: Solution Gap from Lower Bound for Sensitivity Analysis

Delivery Strategy	8 Trucks	12 Trucks	16 Trucks	20 Trucks
Mixed Load	7.45%	34.16%	37.54%	13.28%
Single-Commodity	19.68%	44.57%	67.17%	41.97%

Evaluation of Fairness

Figures 4.19 and 4.20 show demand satisfaction through the percentage of demand fulfilled for the scenario where there are enough cots to fulfill all demand across a range of trucks available to distribute using mixed load delivery. Demand satisfaction occurs more rapidly in counties with a high SVI, and in some scenarios, some counties have fully met demand before other counties receive any commodities. This is considered an issue of fairness because the social vulnerability of a community does not represent individual vulnerability. For example, there could be highly vulnerable individuals and families in counties that do not receive any aid in their county due to their affluent and resilient neighbors. This issue of fairness occurs because the objective is focused on maximizing the utility of the commodities.

The unmet demand was determined using the demand unmet in the final time period, so while Figures 4.19 and 4.20 may indicate that all demand was met, it does not indicate if that demand was met for all time periods in the time horizon.

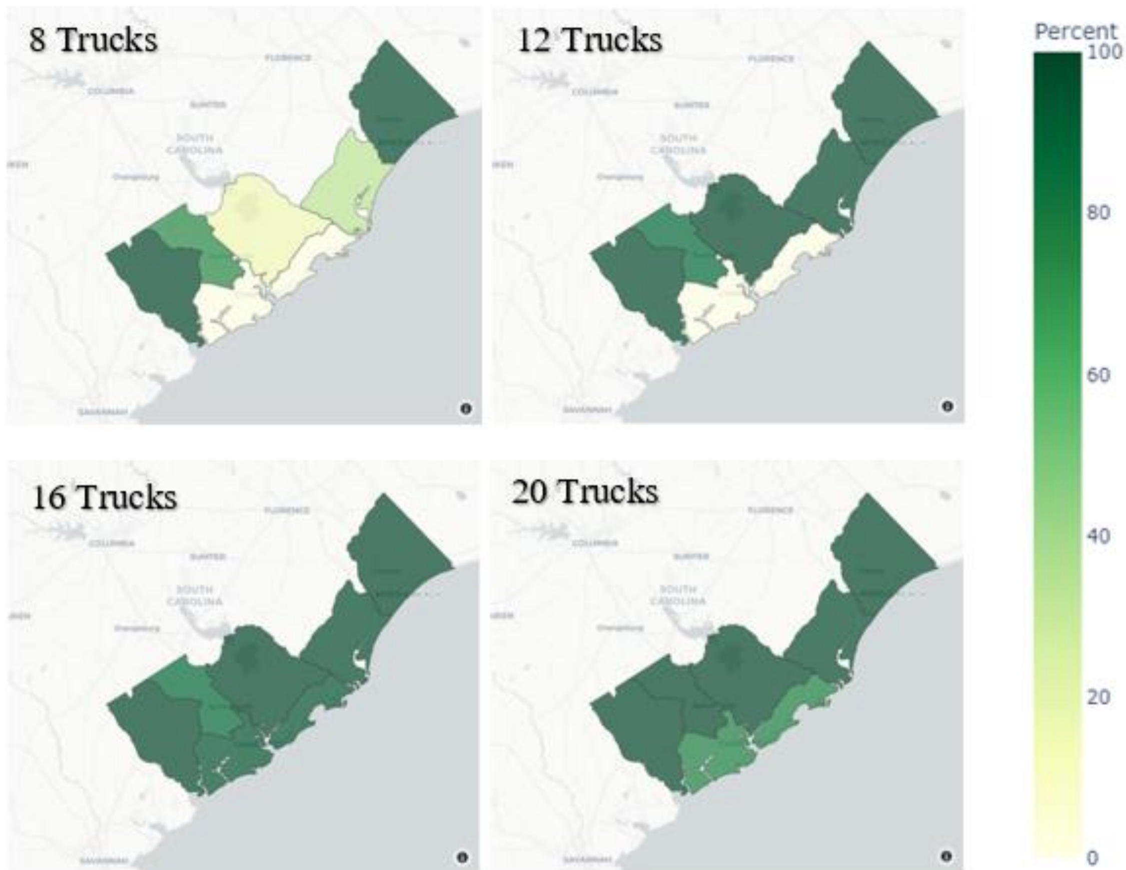
Figure 4.19: Shelter Demand Satisfaction using Mixed

Truck Distribution and No Cot Limitations

In rare cases, demand fulfilled for a county is higher with a lower truck quantity than it is with a higher truck quantity. In the example shown in Figure 4.20, Charleston County has 96% of its demand fulfilled with 16 trucks, but when the number of trucks increases to 20, the demand fulfilled is 78%. This occurs because some trucks used to meet demand when there were 16 trucks are redirected to meet demand in Dorchester County as the number of trucks increases.

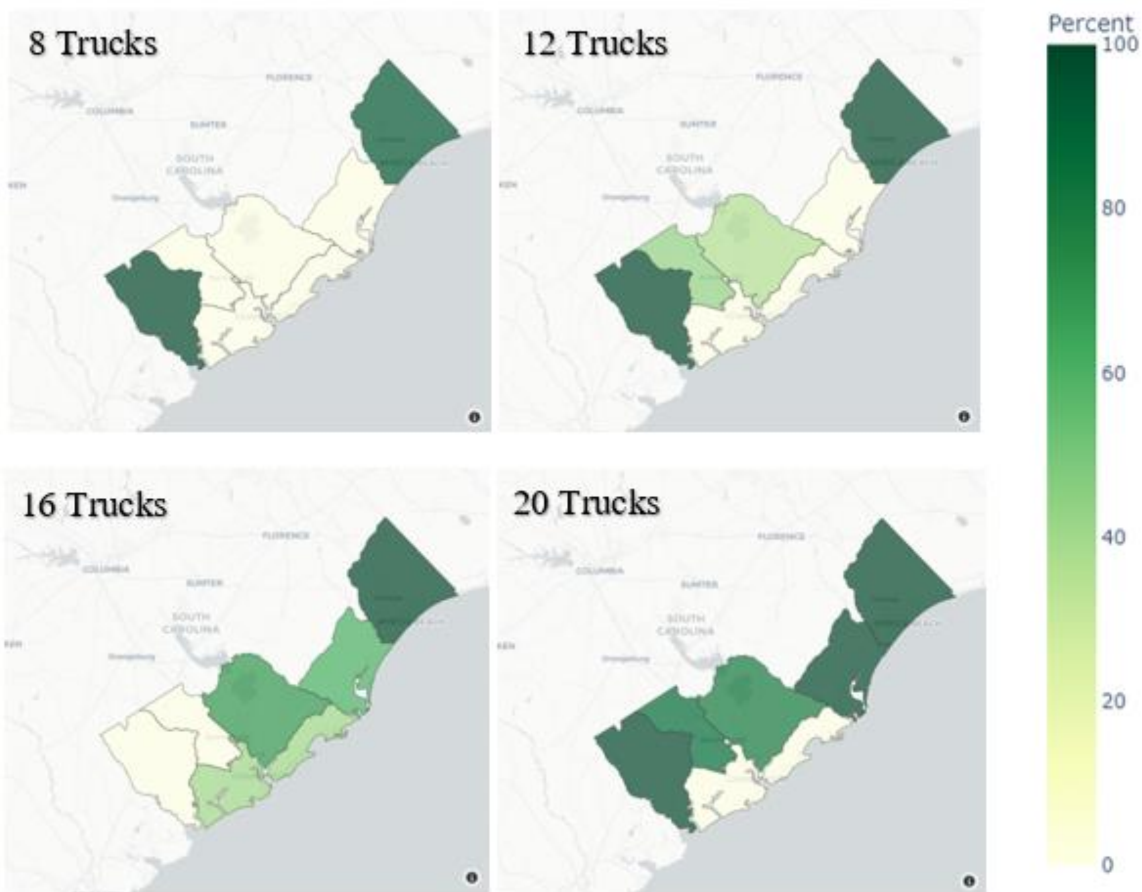
Figure 4.20: PoD Demand Satisfaction using Mixed

Truck Distribution and No Cot Limitations



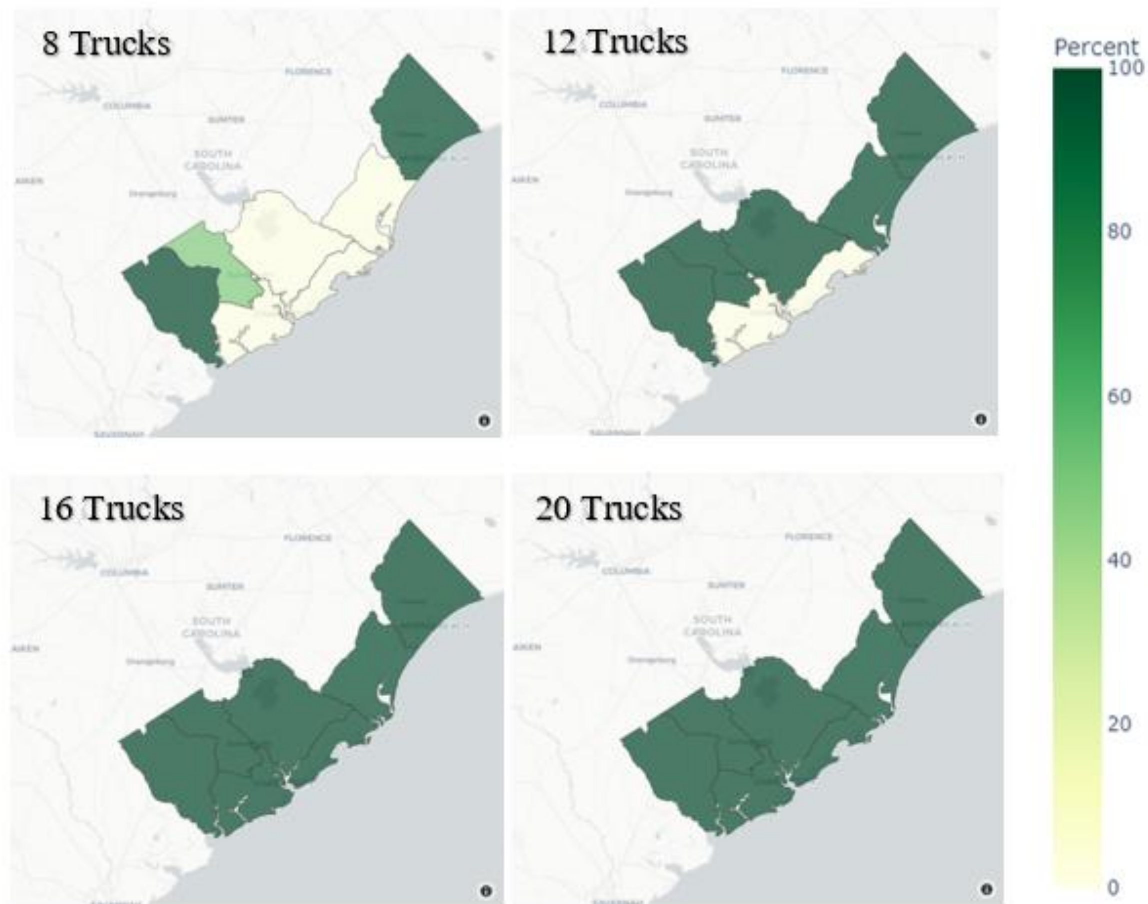
Figures 4.21 and 4.22 are similar to Figures 4.19 and 4.20 but depict a single-commodity distribution strategy. Figure 4.21 shows a drastic example of shifting demand fulfillment between truck quantities 12, 16, and 20.

Figure 4.21: Shelter Demand Satisfaction using Single-Commodity Distribution and No Cot Limitations



In the 20-truck scenario of Figure 4.22, it appears as if all PoD demand is met when, in actuality, the model does fulfill the PoD demand which appears in the final time period of the model.

Figure 4.22: PoD Demand Satisfaction using Single-Commodity Distribution and No Cot Limitations



Map Interactivity and Solution Visualization

Interactive maps depicting the results in Figures 4.19, 4.20, 4.21, and 4.22 allow decision-makers to visualize viable solutions and dynamic demand satisfaction. The Plotly Python library was used to generate visualizations that intuitively zoom and allow for movement within the map. It allows for a draggable, sliding scale to evaluate various truck quantities and their effect on the solution (Figure 3.11). The visualization also allows for county selection and provides the ability to code pertinent information into a popup (Figure 3.12). Solution visualization is an important desire of SCEMD as it can allow them to see the numbers they work with and can help them better understand the consequences of logistical decisions.

CHAPTER FIVE

CONCLUSION

Conclusions

This paper presents models that optimize scenario-dependent logistics plans, provides options for the visualization of logistic solutions, and suggests alternatives to some aspects of the government's current logistics plan, which can aid in the efficiency of the distribution of life-saving supplies. The study found that a mixed load distribution strategy favors SCEMD's prioritization of meeting as much demand as possible, but the difficulty of the mixed load strategy increases depending on suppliers' scenario-dependent distribution. Another conclusion is that the quantity of cots and blankets located in the state could be considered a bottleneck, and future state plans could include the identification of more available cots for disaster scenarios. An overarching finding is that the utility of commodities to demand units when using a social vulnerability-based penalty does not lead to fair distribution. Based on these conclusions, SCEMD could consider adjusting its comprehensive plans to accommodate mixed truck distribution, include additional available cots, and account for fairness under commodity scarcity.

While the models were designed and constrained to accommodate perfect storm and evacuation predictions, they have applications beyond that assumption for post-disaster delivery. There will be demand scenarios in which the models are applicable where decision makers have full knowledge of demand, such as post-disaster sheltering and commodity requirements for hurricanes, earthquakes, or wildfires. The model can also be used with a rolling-horizon approach, solving the problem day by day with realized demand.

Limitations

The main limitation to the accuracy of the model's solutions is the accuracy of the demand inputs. Previous state assumptions were based on the same percentage of demand across all counties, which has been improved upon in this study but is still an assumption input for the model, which affects the results. Inaccuracy in the time-expanded model is related to the long time period utilized to reduce the model's computational complexity.

Another limitation of the models is that they do not have SCEMD's expertise in disaster logistics. These models should be used as a starting point in logistics planning or for practice scenarios but do not replace the experienced decision-makers on the SCEMD team.

Future work

Future work could include creating a stochastic adaptation of the model to account for the uncertainty of if, when, where, and with what magnitude a hurricane could impact South Carolina. It would also be beneficial if options for ensuring fairness under scarcity were further explored. Finally, discussions with SCEMD should continue to determine how the models can be adapted or further constrained to model their decision-making more accurately.

APPENDICES

<u>Appendix A</u>

<u>Conglomerate Data</u>

Figure A-1: Regional Boundaries Used When Referencing Conglomerate Data: These conglomerates were used when referring to data which referenced conglomerates.

Cat 3+ Regional Percentages			
Conglomerate	% Evacuate to public shelter	% Unlikely to evacuate	% Likely to evacuate
Southern	0.109	0.066	0.857
Central	0.19	0.128	0.742
Northern	0.227	0.165	0.707
State	0.178	0.121	0.767

Table A-1: Regional Percentages of Evacuation Actions Based on Conglomerates.[27]

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