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Evaluating the Effectiveness of Prepositioning Policies in Response to Natural Disasters

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ABSTRACT

Recent natural disasters highlight the complexities associated with planning, coordination and distribution of supplies in a manner which provides timely and effective response. In this paper, we present a model to quantify the benefits associated with pre-positioning local supplies. We assume the supplies are in a high-risk location and may be destroyed if an appropriate strategy to protect the supplies is not implemented. A stochastic linear programming model is developed where the first-stage decision pre-positions existing supplies to minimize the supply loss. Second-stage decisions attempt to maximize the responsiveness of the system by allocating supplies to satisfy demand. The benefits associated with pre-positioning versus non-pre-positioning are discussed.

Keywords: *Pre-positioning; Stochastic Programming; network flow; supply damage; humanitarian relief*

INTRODUCTION

Emergency response in large scale, catastrophic events is an emerging area of research in the operations research and management science community. Much of the interest has been sparked by frequently occurring natural disasters, most notably hurricanes Katrina and Rita, the tsunami induced floods in India, and the September 11, 2001 terrorist attacks in New York. Furthermore, logistical failures caused by insufficient planning and inadequate resources are often highly publicized in media outlets. Obtaining sufficient supplies and coordinating the distribution of those supplies can be a significant challenge during the response effort. In this paper, we propose a model to address this supply and demand coordination problem, as it relates to pre-positioning local supplies. While pre-positioning is not a new concept, as the military has used this for quite some time (Johnstone, Hill and Moore, 2004), it is becoming more realizable that pre-positioning is an effective strategy when planning response to natural or man-made disasters. Before the landfall of hurricane Katrina, the federal government implemented methods for pre-positioning supplies which were described as the "largest pre-positioning of Federal assets in history" (Townsend 2006). The gulf coast states also initiated local efforts to pre-position responders and identify shelters in preparation for the storm. In general, pre-positioning is an activity which is performed prior to the event, in which locations are selected to store human or material assets in preparation for a future need. The pre-positioned supplies are subsequently used to satisfy the demand post-event. The model presented in this paper identifies a least-cost strategy associated with pre-positioning existing supplies that may be in a high risk path for a particular event.

Research in the area of humanitarian logistics can be classified based on the nature and timing of the decisions (post-event relief vs. preparedness). The nature of decisions can address distribution of relief supplies (Sheu, 2007, Yi and Ozdamar, 2007), stocking of relief supplies (Beamon and Kotleba, 2006a, 2006b, Lodree and Taskin,2007), or location of supply centers (Jia *et al*. 2005, 2007). Beamon and Kotleba (2006a,2006b) focus on inventory planning for a general type of humanitarian emergency. Lodree and Taskin (2007) incorporate information related to hurricane intensity, specifically wind speed data, into a stochastic inventory planning model. Rawls and Turnquist (2006) develop a more comprehensive model incorporating location, inventory and distribution decisions for a multi-product system. Research such as Sheu (2007), Yi and Ozdamar (2007), and Jia *et al.* (2007), focus on post event relief and response, while the other models focus on preparedness activities. Several of the planning models that address the optimal placement of resources extend existing facility location and supply chain network design models to incorporate the uncertain characteristics associated with the disaster. Refer to Snyder *et al*. (2006) for a good discussion of network design models under uncertainty. Jia *et al.* (2007) develop a model to determine the location of medical services during large scale emergencies. They characterize large-scale emergencies as those that have a sizeable and sudden volume of demand and low frequency of occurrence. They introduce two parameters to characterize this uncertainty and propose location models to (1) maximize the demand covered by a certain number of facilities, (2) minimize the demand weighted distance between the new facilities and the demand points, and (3) minimize the maximum service distance. Rawls and Turnquist (2006) also incorporate location decisions in their model. They consider a multi-commodity pre-positioning and location problem to satisfy demand resulting from a hurricane. The objective is to find the number of new facilities to open, the size of the facilities and the purchase quantities associated with the three commodities considered. The problem is formulated as a stochastic mixed integer programming model with uncertainty in demand, damage to roads, and damage to facilities determined from hurricane scenarios. The research presented in this paper compliments the work done in this area and builds on the work of Rawls and Turnquist (2006). We consider a single commodity supply network that is already established and contains initial amount of inventory to satisfy demand due to normal operations. Therefore, no location decisions are made. We consider uncertainty in demand and available supply and use a stochastic linear programming model to determine the placement of supply within the network to minimize supply loss. Uncertain demand in transportation planning has also be considered by Sumanta and Jha (2011) and Murakami and Morita (2010). However, this paper focuses on inventory placement and distribution, rather than vehicle utilization.

Stochastic linear programming models (SLP) are linear programming models where uncertainty associated with one or more of the problem data exists; and decisions must be made in such a way that they are balanced against the uncertain data scenarios. Decisions that can be delayed until after some of the uncertainty has been revealed are called recourse models (Higle, 2005). In the general model we have a set of decisions to be taken without full information on some random events. These decisions are called first-stage decisions. Later, full information is received based on the realization of some random vector and second stage or corrective actions are taken. The objective is to minimize the summation of (1) the cost associated with the first stage decision and (2) the expected cost associated with the scenario-specific second stage decision. The reader is referred to Birge (1997) and Higle (2005) for a more comprehensive discussion on stochastic linear programming models. The remainder of the paper is organized as follows. The model and assumptions are described in the next section. We then present the experimental design followed by a discussion of the computational study. Finally, we summarize the key insights and discuss limitations and opportunities for future work.

PROBLEM DEFINITION

Assumptions

We consider the situation where the supply locations and capacities are known and contain an initial level of inventory to satisfy demand due to normal operations. After an event, such as a hurricane, the inventory is subsequently used in the response effort to satisfy the demand requirements of the affected population. The level of demand is affected by the nature of the event and is thus different from the expected demand during normal operations. This is typical for a relief organization such as a network of food banks, which satisfy demand daily and during disasters. As an event strikes an area, a fraction of the stored supplies may be damaged. This is a reasonable assumption since an event has the potential of damaging structures; If a structure storing the supplies is damaged, then some or all of the supplies within the facility may be damaged. A realistic illustration of this scenario is reported in America’s Second Harvest Katrina Report (America’s Second Harvest, 2005). 8-12% of the food pantries, kitchens, and shelters served by America’s Second Harvest Network were no longer in operation following the Hurricane, and the New Orleans food bank suffered damage and was inaccessible due to flooding.

We formalize the problem assumptions as follows.

1. Consider a supply and demand network consisting of a set of *N* supply nodes and *H* demand nodes.
2. Each supply node, $n \in N$, corresponds to a facility such as a warehouse or distribution center with the purpose of holding large amounts of supplies.
3. Each supply facility can store a limited number of supplies due to the maximum physical volume allowed. A portion of this total available space is allotted to initial inventory (assumed known) in use for normal operations.
4. The set of demand nodes, $h \in H$, represent locations or physical structures that may be used to provide relief to victims after the occurrence of some event (natural disaster or terrorist activity).
5. Prior to the event, an initial demand forecast for items supplied by the facilities is known and reflects an estimate of the population that can be served at a demand location. The supply is just enough to fulfill the demand in the areas served by the facilities.

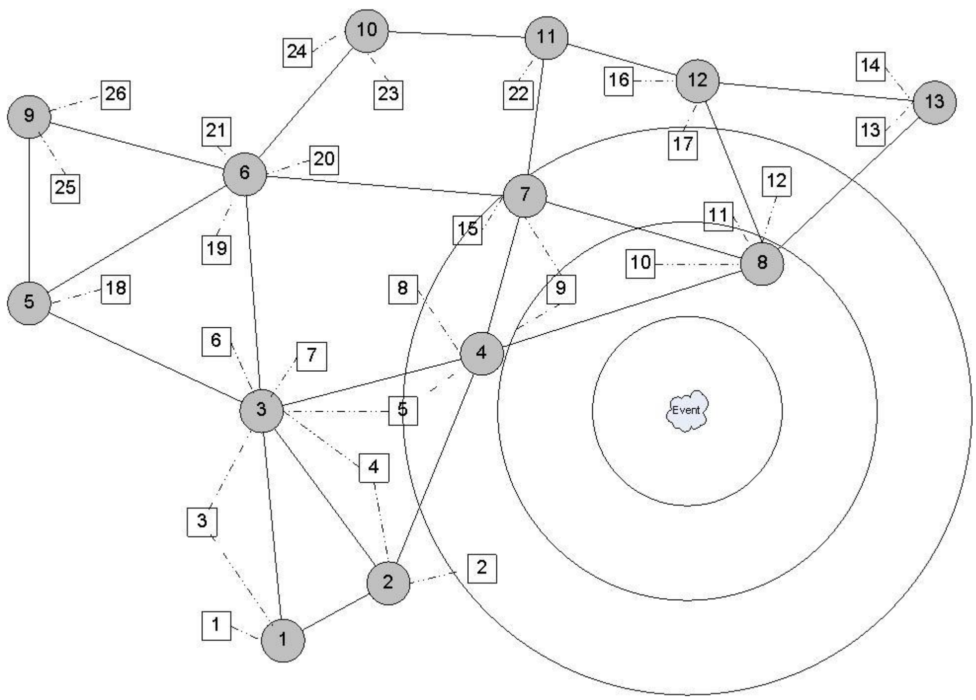


Figure 1. Supply and Demand Node Network (SouthEastern United States)

6. After an event, the actual quantity demanded may increase, decrease or stay the same. The relative change in the initial demand forecast is approximated by a discrete distribution. The level of change is dependent on the demand node's proximity to the event path and the level of severity of the event;
7. Similarly, the supply at a supply node after an event may decrease due to facility damage or stay the same. The relative decrease in the supply is approximated by a discrete distribution. The level of decrease is dependent on the event severity and the supply node's proximity to the event path;
8. Supply nodes that are closer to the event path are assumed to sustain the most damage. In Figure 1, supply node 3 would experience a greater change in supply than nodes 6 or 13;
9. Interconnections between the supply nodes represent physical transportation routes between facilities such as interstate or state highways. These connections are utilized in both the pre-positioning and response stages of the model. Usually each of these arcs will also have limitations. In this model, a specific limit on an arc is not considered.

We assume the decision maker has some foreknowledge about the event and seeks to take a proactive approach to planning distribution of supplies after the event. Prior to the event occurrence, supplies are transported between supply nodes only, where capacity is available. After the event occurrence, supplies are shipped between supply and demand nodes to satisfy demand. Figure 1 captures the supply and demand network described above, with shaded nodes denoting supply facilities and unshaded nodes denoting demand locations, such as shelters.

Formulation

We develop a two-stage recourse model where the first-stage decision corresponds to the pre-positioning decision and is made prior to the event. The second-stage decision is made after the event has been realized and is referred to as the response phase. These two phases adequately characterize the planning and response phases of an emergency planner. We adopt the notation of Higle (2005) and denote a specific realization of the event (scenario) by ω with associated likelihood parameter p_{ω}. The first-stage decision variables, second-stage scenario specific decision variables and associated model parameters are presented below.

First-stage decision variables:

S_n: stored (pre-positioned) quantity of supplies at supply node n.

x_{nj}: quantity of supply units shipped from supply node n to supply node j, $n, j \in N$.

Second-stage Decision Variables:

$u_{h,\omega}$: unmet demand quantity at node h, per scenario ω.

$w_{nj,\omega}$: quantity of supplies shipped from supplier n to supplier j, per scenario ω.

$y_{nh,\omega}$: quantity of supplies shipped from supplier node n to demand node h, per scenario ω.

Supply node parameters

I_n: initial inventory stored at supply node n.

C_n: storage capacity at supply node n.

g: unit cost for supplies.

d_{nj}: unit transportation cost from supply node n to supply node j.

Demand node parameters

F_h: forecasted demand at demand node h prior to the event.

v_h: unit cost for unmet demand at demand node h.

d_{nj}: unit transportation cost from supply node n to supply node j.

t_{nh}: unit transportation cost from supply node n to demand node h.

Supply and Demand changing factors

$R_{n,\omega}$: supply changing factor at supply node n per scenario ω.

$\gamma_{h,\omega}$: demand changing factor at demand node h per scenario ω.

The supply changing factor represents the proportion of supply not damaged by an event. This implies the available supply after an event (ω) is defined as $R_{n,\omega} * S_n$. Similarly, we define the post-event demand using the demand changing factor. This changing factor represents the relative increase/decrease over the initial demand forecast (F_h) as a result of the event. Therefore, the post-event demand ($\gamma_{h,\omega} * F_h$) can be interpreted as the population of the given area that will be affected and thus in need of relief supplies. In the specific case of hurricane Katrina, it can be thought to be the number of individuals that remained after evacuation notices. The cost of potential loss of life due to insufficient supplies is represented as a penalty cost for unmet demand. In practical situations, this parameter can reflect the cost required to acquire the goods from another source at a potentially higher cost.

Using the notation defined above, we formulate the two stage stochastic linear programming model as follows.

Min $Z = \sum_n \sum_j x_{nj} * d_{nj}$

$$+ \sum_{\omega \in \Omega} p_\omega * \{ \sum_n \sum_h y_{nh,\omega} * t_{nh} + \sum_n \sum_j w_{nj,\omega} * d_{nj}$$
$$+ \sum_h u_{h,\omega} * v_h + \sum_n S_n * (1 - R_{n,\omega}) * g \} \quad (1)$$

subject to

flow balance for pre-positioning

$$\sum_j x_{nj} + S_n = \sum_j x_{jn} + I_n \quad \forall n \in N \qquad (2)$$

Pre-positioned storage capacity

$$S_n \le C_n \quad \forall n \in N \qquad (3)$$

Post-event supply constraint

$$\sum_j w_{nj,\varpi} + \sum_h y_{nh,\omega} \le S_n * R_{n,\omega} + \sum_i w_{in,\omega}$$
$$\forall n \in N, \omega \in \Omega \qquad (4)$$

Demand Requirement

$$\sum_n y_{nh,\omega} + u_{h,w} = F_h * \gamma_{h,w}$$
$$\forall h \in H, \omega \in \Omega \qquad (5)$$

Non-negativity constraints

$$x_{nj}, w_{nj,\omega}, y_{nh,\omega}, u_{h\omega}, S_n \ge 0$$
$$\forall\, n, j \in N, h \in H, \omega \in \Omega \qquad (6)$$

In the objective function (1), the first term captures the first-stage cost associated with pre-positioning and the remaining terms represent the expected second-stage costs including redistribution cost between supply nodes, distribution cost from supply nodes to demand nodes, supply shortage cost, and pre-positioned supply loss cost. Minimizing the total cost ensures that the minimal amount of supplies moved from initial supply facilities to safer locations (based on $R_{n,\omega}$) and redistribution of the supplies (via supplier to supplier movement, $w_{nj,\omega}$, and supplier to demand movement, $y_{nh,\omega}$) to minimize unmet demand is performed. The first-stage shipments required to pre-position supplies to safer locations are constrained by flow balance equations (2) where the summation of the outbound flows and pre-positioned supply quantity equals the summation of the inbound flows and initial inventory. Furthermore, constraints (3) guarantee that the pre-positioned supply does not exceed the physical storage capacity of the facility. The second-stage flow balance constraints (4) are modeled in a similar manner to the first-stage flow balance constraints with a larger network now including supplier to supplier and supplier to demand shipments. Constraints (5) capture the supply and demand requirement. Finally, we include the typical non-negativity constraints (6) on all decision variables.

EXPERIMENTAL DESIGN

Experimental Design

The intent of this research is to understand the impact of implementing a local pre-positioning strategy when the stored relief supplies may be near the event center. Specifically, we are interested in the following:

1. Quantifying the benefit of pre-positioning in terms of cost and unmet demand quantity;
2. Understanding the sensitivity of the solution to the initial supply level and storage capacities at the supply nodes.

Table 1 summarizes the test cases constructed to address the objectives posed above. The model parameters affected by each experiment are shown as well.

The benefit of implementing a pre-positioning strategy is determined by comparing the difference in cost and unmet demand quantity between the pre-positioning policy obtained from the model, and no pre-positioning policy. No pre-positioning policy is simply the case where no supplier to supplier movements occur prior to the event. This implies $x_{nj} = 0$ for all $n, j \in N$. The cost and unmet demand quantity associated with no pre-positioning policy are determined by minimizing the expected second-stage cost when considering post-event supply constraints, demand requirement constraints, and non-negativity constraints (constraints 4, 5, 6) with the pre-positioned amount at a node (S_n) equal to the initial inventory (I_n).

Model Data and Scenario Generation

Data and scenarios used in the experiment are generated by considering possible hurricane events, similar to that of Hurricanes Katrina or Rita. Each scenario is constructed using a combination of the event severity and the corresponding effect on the supply and demand changing factors (termed a reaction case). Six event severity levels and five reaction cases are considered, yielding a total of 21 possible scenarios (Table 3). Note, we consider the case of no hurricane as one of the event levels which contains only one valid reaction case.

The reaction case considers variations in pre-positioned supply and the initial demand forecast as a result of the event. The change in the demand for supply reflects the public's reaction to the magnitude of the event. The reaction cases and corresponding assumptions are summarized in Table 2.

Table 1. Experimental Design

Experiment	Description	Initial Inventory	Storage Capacity	Pre-Positioning
1.1	Base Model	$\sum_n I_n = \sum_h F_h$	$C_n = 2 * I_n$	$x_{nj} = 0 \quad \forall n, j \in N$
1.2	Base Model with pre-positioning policy	$\sum_n I_n = \sum_h F_h$	$C_n = 2 * I_n$	
2.1	Initial Inventory Increase	$\sum_n I_n > \sum_h F_h$	$C_n = 2 * I_n$	$x_{nj} = 0 \quad \forall n, j \in N$
2.2	Initial Inventory Increase with pre-positioning policy	$\sum_n I_n > \sum_h F_h$	$C_n = 2 * I_n$	
2.3	Initial Inventory Decrease	$\sum_n I_n < \sum_h F_h$	$C_n = 2 * I_n$	$x_{nj} = 0 \quad \forall n, j \in N$
2.4	Initial Inventory Decrease with pre-positioning policy	$\sum_n I_n < \sum_h F_h$	$C_n = 2 * I_n$	
3.1	General Network Capacity Increase	$\sum_n I_n = \sum_h F_h$	$C_n = 2.4 * I_n$	$x_{nj} = 0 \quad \forall n, j \in N$
3.2	General Network Capacity Increase with pre-positioning Policy	$\sum_n I_n = \sum_h F_h$	$C_n = 2.4 * I_n$	
3.3	Safe Node Capacity Increase	$\sum_n I_n = \sum_h F_h$	$C_6 = C_9 = C_{10} = C_{11} = 660$	$x_{nj} = 0 \quad \forall n, j \in N$
3.4	Safe Node Capacity Increase with pre-positioning Policy	$\sum_n I_n = \sum_h F_h$	$C_6 = C_9 = C_{10} = C_{11} = 660$	

Table 2. Supply and Demand Level Change Matrix

Reaction Case	**Supply Change**	**Demand Change**	**Assumption**
1	Decrease	No Change	Structural integrity is compromised and thus supply decreases. The level of decrease depends on the event severity.
2	Decrease	Increase	Demand increases because warnings may have been ignored and the number of actual victims is larger than expected. Structural integrity of supply centers is compromised.
3	Decrease	Decrease	Demand forecast decreases due to a false alarm (for category 1 or 2 event) or because the number of victims is less than expected. Structural integrity of supply centers is compromised.
4	No Change	Increase	Event causes little structural damage and thus supply is not affected. Demand increases due to overreaction by the affected population.
5	No Change	No Change	Event has no affect on the supply or demand, which is only true if the event does not occur.

Table 3. South Eastern United States Hurricane Testing Scenarios

Event	P(Event)	Reaction Case	P(Reaction Case|Event)	Ω	P(ω)
No Hurricane	0.30	5	1.00	ω1	0.300
Category 1	0.15	1	0.32	ω2	0.048
		2	0.32	ω3	0.048
		3	0.04	ω4	0.006
		4	0.32	ω5	0.048
Category 2	0.20	1	0.1	ω6	0.020
		2	0.6	ω7	0.120
		3	0.1	ω8	0.020
		4	0.2	ω9	0.040
Category 3	0.28	1	0.3	ω10	0.084
		2	0.4	ω11	0.112
		3	0.1	ω12	0.028
		4	0.2	ω13	0.056
Category 4	0.05	1	0.05	ω14	0.0025
		2	0.75	ω15	0.0375
		3	0.15	ω16	0.0075
		4	0.05	ω17	0.0025
Category 5	0.02	1	0.1	ω18	0.002
		2	0.74	ω19	0.0148
		3	0.15	ω20	0.003
		4	0.01	ω21	0.0002

Using the number of landfall hurricanes per year and the categorization of the Saffir/Simpson Hurricane Scale, a discrete distribution is derived (Louisiana, 2007). This is only used as a working approximation of the likelihood of occurrence. For a more accurate evaluation when adopting this model, meteorological forecasts can be used to determine the probability of each category of hurricane striking land. For each possible hurricane category, we construct a conditional distribution for the set of reaction cases. The corresponding scenario probabilities are the product of these two probabilities as shown in Table 3.

For each node and each scenario, the supply and demand changing factors are varied based on the distance the node is from the center of the event and the event severity. Supply nodes closest to the event (such as supply nodes 1, 2, 4, 8 and 13 of Figure 1) sustain the most loss while nodes farther from the event (such as supply nodes 9 and 10) sustain the least. Both supply loss and demand increase at the respective supply and demand nodes as the hurricane severity increases.

Initial values for the model parameters are summarized in Table 4. The initial inventory is equal to the forecasted demand, based on the assumption that the demand forecast is correct and just enough supplies are available to fulfill that demand. Since transportation cost is approximately proportional to transportation distance, the unit transportation costs between nodes, t_{nhm} and d_{nj}, are estimated based on the Euclidean distance between nodes. The distance and supply node changing factors used for the experiment are available in Chapman (2007). It should be noted that the experimental values for supply and demand are chosen so that the relationship between the two can be explored.

Table 4. Parameter values for Base Model

Parameter	Value
I_n	200
F_h	100
C_n	400
v_h	\$100
G	\$1000

RESULTS AND DISCUSSION

Experiment 1: Base Model SLP Policy Evaluation

Figure 2 illustrates the capability of the supply network to satisfy demand in each of the defined scenarios. The fraction of unmet demand per scenario is lower when a pre-positioning policy is used. The largest benefits correspond to the scenarios where supply is reduced as a result of damage to the supply nodes. The results also indicate increasing the forecasted demand with no resulting damage to supply yields no difference in the fraction of unmet demand between the 2 policies (Scenarios 5, 9, 13, 17).

The total cost associated with using the pre-positioning policy is \$120,630 consisting of a first-stage pre-positioning cost of \$4,760. The expected cost associated with not using a pre-positioning policy is \$242,200 (Table 5). Utilizing the pre-positioning policy results in a 49.8% reduction in expected system costs and improves the expected demand fulfillment. Figure 3 shows the resulting supply and demand network when both no policy and the pre-positioning policy are implemented. The figure illustrates that using the SLP model results in movement of supplies from riskier nodes to safer nodes.

Table 5. Summary of Experimental Results

Experiment	Expected Unmet quantity	Cost: First Stage	Cost: Second Stage	Cost: Combined Cost	Percent Improvement: /no policy[1]	Percent Improvement: /policy[2]
1.1	298	Na	$242,200	$242,200		
1.2	191	$4,760	$115,870	$120,630	49.8%	
2.1	110	Na	265,670	265,670		
2.2	67	$4,672	$149,720	$154,390	58.1%	128.0%
2.3	777	Na	$247,730	$247,730		
2.4	665	$4,504	$126,790	$131,290	53.1%	108.8%
3.1	298	Na	$242,200	$242,200		
3.2	175	$5,528	$97,178	$102,710	42.4%	85.1%
3.3	298	Na	$242,200	$242,200		
3.4	165	$4,816	$82,064	$86,880	35.9%	72.0%

[1] Percent improvement of experiments combined cost over using no policy for the experiment
[2] Percent improvement of experiments combined cost over experiment 1.2, base model

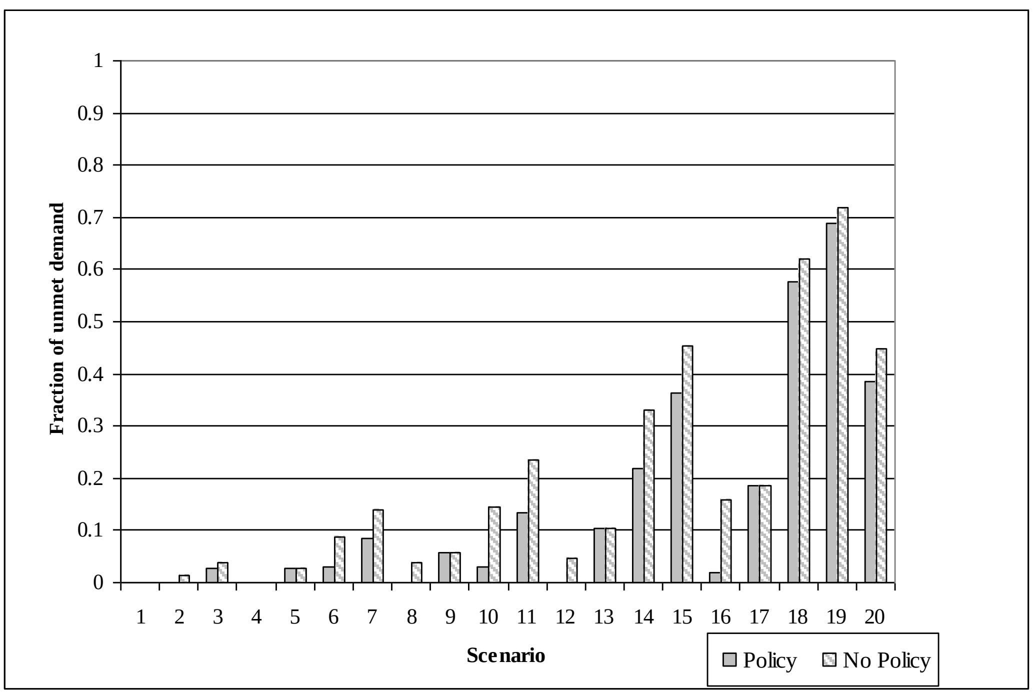
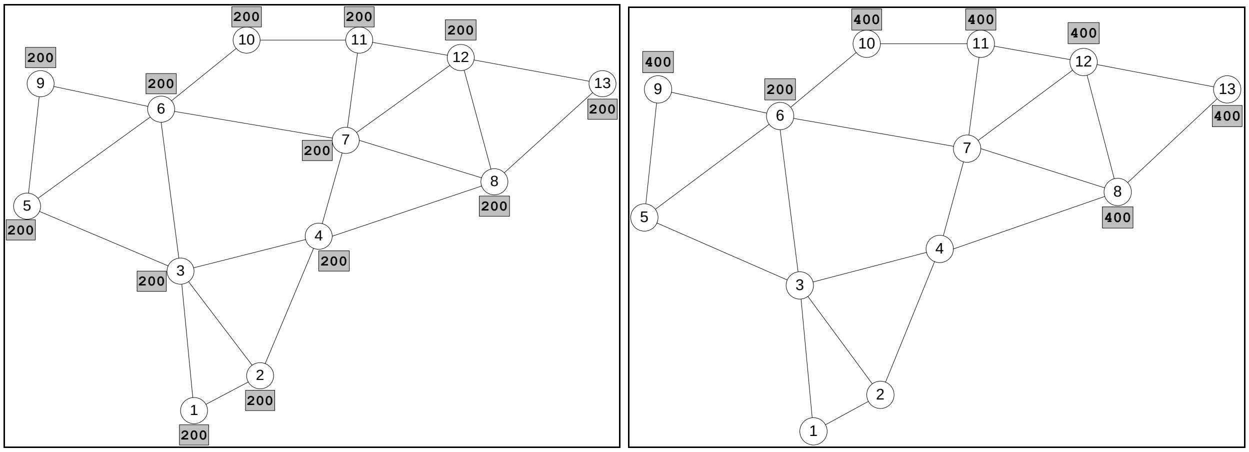


Figure 2. Fraction of unmet demand per Scenario



(a) (b)

Figure 3. (a) South Eastern United States No Policy (b) South Eastern United States Pre-positioning Solution

Experiment 2: Initial Inventory Variation

In an actual event, pre-positioned supply is potentially damaged and there is some change in demand. With this, it would be impractical to assume that the actual demand would be met. Increasing initial inventory would yield a higher resultant supply able to fulfill more actual demand. Conversely, decreasing the initial supply would have a two-fold impact on the ability of the network to satisfy demand. First, the difference in initial supply and forecasted demand would already ensure there will be unmet demand. Second, the changes in demand and available supply due to the event would further hinder responsiveness.

Using the parameters of experiment 1.2 as a base, the initial inventory values per node are changed to determine the effect on the pre-positioning solution. A 20% increase and 20% decrease in initial inventory are applied across all supply nodes. An increase in the initial quantity stored at a supply node, with no increase in capacity, results in less space for incoming supplies. This becomes an issue at the safer nodes where the decrease in storage space for inbound supplies results in the SLP utilizing less safe nodes to pre-position. The trade off is that there will still be a comparable quantity of supplies stored at safer nodes. Figures 4 (a) and (b) display the effect changes in initial inventory have on the pre-positioning solution.

Logically, having more initial inventory results in a higher resultant supply thus a lower expected unmet demand quantity. This is reflected in Table 5, where the expected unmet demand is lower in this experiment than in the previous one. However, the overall system execution cost is higher. Increasing the initial inventory increases the system wide supply quantity. In such a case, the system has more that it can risk when pre-positioning. The pre-positioning solution illustrates that the SLP will fill to capacity the nodes it determines to be safest and in descending order, fills in the next safest nodes. Compared to the solution from experiment 1.2, more risky nodes are used as a result of the supply increase and therefore larger supply losses are incurred. Therefore, a higher cost associated with damaged supplies is realized. In both cases, using the pre-positioning policy provides significant improvement over not using a pre-positioning policy. The percentage reduction for both cases is over 50% (Table 5).

Experiment 3: Supply Node Capacity Variation

Experiment 3 considers an increase in the storage capacity of each node. The initial supply level is defined from experiment 1.2. Two cases are considered: (1) a general network-wide increase of 20% for each supply node's storage capacity; and (2) increasing the capacity of the safest nodes. Relative to the base model, both experiments are increased by the same percentage. The summation of the storage capacity for experiments 3.1 and 3.2 will equal that of 3.3 and 3.4.

In the opposite way that increasing the initial inventory resulted in a reduced amount of storage space, an increase in capacity results in more space at safer nodes for pre-positioned supplies. Therefore, the SLP model tends to fill safer nodes to capacity which has the end result of a larger safer pre-positioned quantity. This benefit is reflected in both experiments.

Compared to the combined/objective function cost of experiment 1, increasing the storage capacity had the greatest effect on reducing the cost and unmet demand. It can be reasoned that this is due to the SLP's capacity loading of safer nodes. When there is more space at a safer node, then a smaller portion of the initial inventory is subject to be damaged by the event. The solution's facility usage due to this can be seen in Figures 4 (c) and (d).

CONCLUSION

This research proposed a two-stage stochastic network flow model to derive a pre-positioning and emergency response policy based on the probability of an event. The results demonstrate employing some pre-positioning policy is beneficial in maintaining a sufficient supply quantity post-event (Table 5). Logically, the act of pre-positioning caused by the SLP, moves supplies away from nodes that are likely to incur the highest level of damage to ones that are "safer".

Initial inventory has a significant effect on the performance of the SLP policy in an actual event. Increases in initial inventory directly correlate to the total resultant supply of the network. Quite naturally, having more supply will increase the likelihood of satisfying demand. Greater response (through demand fulfillment) and less supply loss can be realized if there is sufficient capacity in the "safe nodes". When capacity is insufficient (or unavailable) to store the additional inventory, the system execution cost can be higher due to the disproportion between the unmet demand cost of $100 and the unit cost of $1,000 used to calculate the loss cost. As a result of these settings, an exaggerated cost is achieved for what could be interpreted as a good solution, relative to unmet demand. If the goal is to maximize responsiveness by reducing the unmet demand, then the unmet demand cost should be higher than the unit cost. The initial reasoning for the cost parameter settings was to minimize the supply loss due to event damage, and thus increase the resultant supply quantity. This slight nuance may be an avenue for future investigation.

The outcome of the SLP model is highly dependent on the input data. The manner in which the supply damage and demand change ratios are defined per node, permits various other circumstances to be evaluated. Careful manipulation of these per node values can be used to model not only magnitude of an event such as a hurricane, but also the direction. The use of node specific penalty costs can also be used to model prioritized demand fulfillment. Additionally, utilizing actual demand distributions instead of a randomly

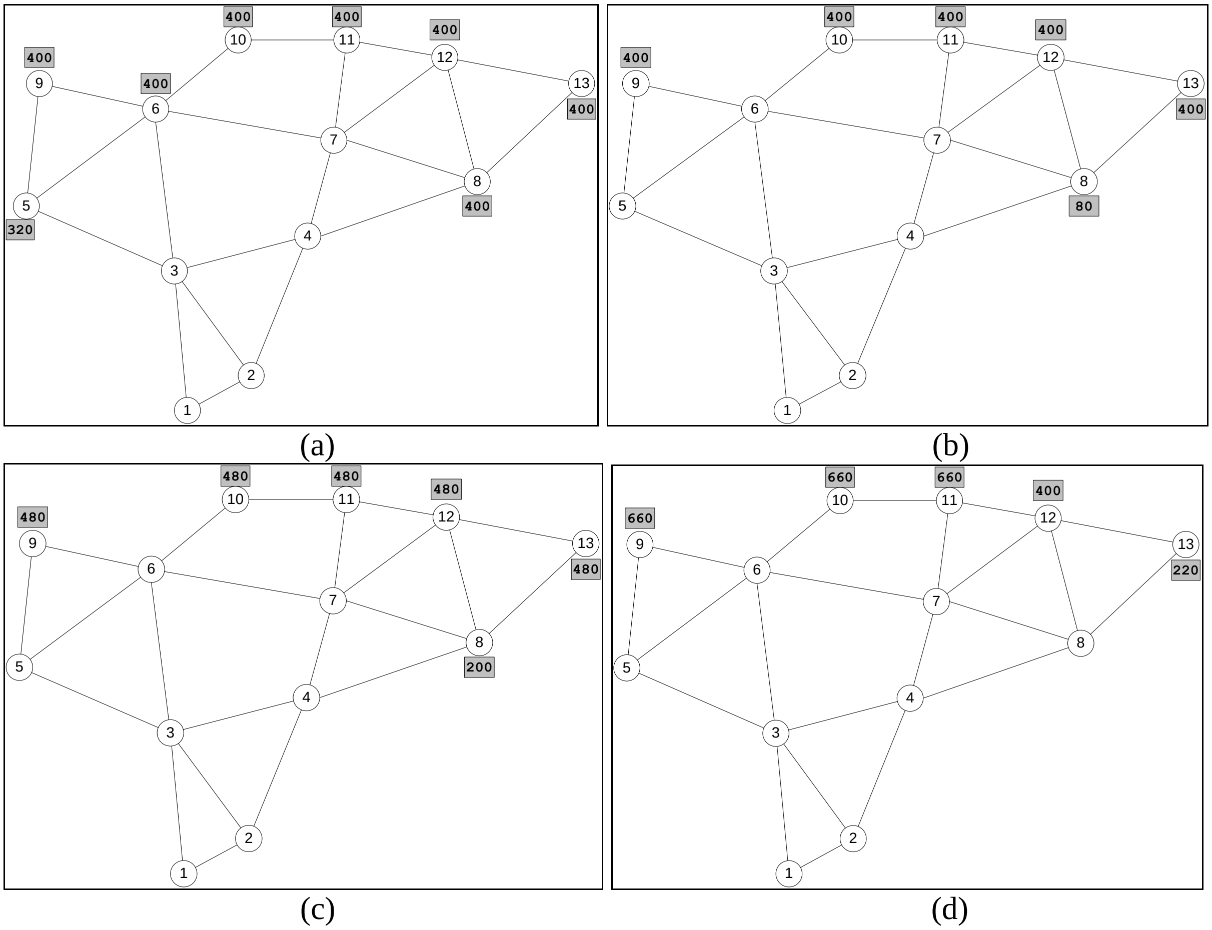


Figure 4. (a) Initial Inventory Increase Pre-positioning Solution (b) Inventory Decrease Pre-positioning Solution (c) General Network Capacity Increase Pre-positioning Solution (d) Safer Node Capacity Increase Pre-positioning Solution

generated distribution may increase the fidelity of the model and provide additional insights.

Not investigated in this research are variances in cost. Network costs such as the supplier to supplier and supplier to demand node costs are assumed to be the same pre and post event. This is based on the assumption that demand fulfillment rather than monetary costs should be the priority in an emergency situation. Varying the cost parameters between first and second stage may provide additional insight.

Incorporation of other costs may also be another extension of this research. Here, the holding costs are neglected, again, based on the assumption that demand fulfillment is the top priority. However, it is more realistic to assume that each facility will incur some holding costs associated with the pre-positioned supplies. This may be more applicable in situations where the supply facilities are not all owned by the same organization, possibly resulting in some increased cost or an additional fixed cost to lease the space.

Lastly, this model is limited because of the assumption that the transportation time is negligible. The distance is used as a cost, however, given a short window of opportunity to react to a potential event, such massive movements of supplies may be difficult to realize. Supply movements can be further complicated if roads are severely damaged. Damage to roads and the impact on traffic congestion is an area of future work.

Supply chain management of emergency response to disasters is an emerging area of research. Future work should consider the integration of all the activities along the supply chain from procurement to distribution.

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