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Inventory planning and coordination in disaster relief efforts

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ABSTRACT

This research proposes a stochastic programming model to determine how supplies should be positioned and distributed among a network of cooperative warehouses. The model incorporates constraints that enforce equity in service while also considering traffic congestion resulting from possible evacuation behavior and time constraints for providing effective response. We make use of short-term information (e.g., hurricane forecasts) to more effectively preposition supplies in preparation for their distribution at an operational level. Through an extensive computational study, we characterize the conditions under which prepositioning is beneficial, as well as discuss the relationship between inventory placement, capacity and coordination within the network.

1. Introduction

Coordinating emergency supplies during the aftermath of a disaster is one of the main challenges associated with immediate response efforts. Information about available resources is often unknown and contributions of suppliers can be unpredictable (Kovacs and Spens, 2007). Adding to the challenge is the fact that the disaster relief environment in large-scale, catastrophic events often involves many actors such as non-governmental organizations (e.g. Red Cross); various local, state, and federal government agencies (e.g. FEMA); faith based organizations (e.g. churches); and firms in the private sector (e.g. local grocers). Some organizations function autonomously providing specialized products (e.g. food, water) or services (e.g. medical assistance, sheltering.). Others work within a larger collaborative structure led by either the governmental authority of the affected area (NRF, 2008) or a coordinating agency such as the United Nations Joint Logistics Center (Kaatrud et al., 2003; Balcik et al., 2010).

Most scholars agree that coordination can improve effectiveness of initial response efforts (e.g. Stephenson, 2005; Van Wassenhove, 2006; Chandes and Pache, 2010; Balcik et al., 2010). However, coordination can also be quite challenging as evidenced by the Indian Ocean tsunami. The relief operation for this particular disaster was described as "chaotic" due to the large influx of new and inexperienced organizations and volunteers, an overwhelmed government, and an absence of regulatory measures to control and manage the entry of volunteers and goods (Van Wassenhove, 2006).

A number of quantitative models in the disaster relief literature have addressed issues related to inventory management such as inventory placement/prepositioning, determining quantities of relief supply to stock in advance of a disaster, and determining how the inventory should be distributed post-disaster. However, inventory coordination during disaster relief efforts has largely been unexplored. There is some evidence that inventory coordination in the form of sharing information and/or warehouse space occurs during disaster relief efforts (Balcik et al., 2010). For example, the UN Humanitarian Response Depot supports strategic stockpiling efforts of the UN, international, governmental and non-governmental relief organizations (www.hrdlab.eu). The state of Florida has a logistics warehouse to coordinate the efforts of state and federal responders (SLRC, 2012). However, many non-governmental organizations that participate in disaster relief have their own warehouse network where they stock supplies. For example, Feeding America, a non-profit hunger relief organization, has warehouses across the United States where they receive donated food. Some faith based organizations (e.g. Church World Service, United Methodist Committee on Relief) that participate in disaster relief activities through the Voluntary Organizations Against Disasters (VOAD) own warehouses that stock relief supplies. Coordination among these various participants requires accurate information as well as frequent communication regarding the availability of their resources. Better planning and information regarding disaster resources will help to eliminate redundancy, duplication of effort and potentially unused supply.

In this paper, we address inventory management decisions in the context of coordination. Specifically we consider the problem

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of prepositioning local and external supplies within a cooperative distribution network prior to an upcoming natural disaster, such as a hurricane. The term *local* refers to supplies that are stored close to the affected area and perhaps managed by a local governmental authority. *External supplies* refer to those goods available from an outside agency. We define a *cooperative distribution network* as a group of entities who normally act autonomously, but under severe disaster conditions, try to come together to provide assistance and aid to the affected population. We explore a specific coordination structure characterized by two parameters: reserve capacity (warehouse space) and inventory commitment (relief supplies) and identify conditions under which coordination and supply allocation decisions are beneficial. We take into consideration road congestion resulting from (i) pre-disaster evacuation activities and (ii) post-disaster road damage.

Prepositioning is not a new concept, as the military has used this for quite some time (Johnstone et al., 2004). However, it is becoming more widely studied and applied in the context of emergency response (e.g. Duran et al., 2011; Lodree and Taskin, 2009; Rawls and Turnquist, 2010). The majority of the research on prepositioning occurs at the strategic level addressing long-term supply network decisions such as where to establish supply locations, and how much material to stock there. The best location is weighed against disaster uncertainty (demand for resources) through the use of probability distributions that represent the likelihood of potential disaster scenarios. The majority of the data used to determine these probability distributions are historical in nature; that is they do not often incorporate information such as forecasted hurricane paths that affect the probability a particular site will be affected by a disaster. The model presented in this paper incorporates forecasted hurricane path and intensity to determine how best to preposition supplies in an established single commodity supply network where one or more of the nodes is in a high-risk path for a particular event. This situation could arise either when strategic prepositioning decisions have been made, or when an existing network is already used to service the community. Since the network under consideration already exists, the problem we consider makes no location decisions. We instead consider the relocation of supplies in advance of a disaster to minimize the possible destruction of those goods, and to aid the distribution of supplies to service those affected by the disaster after it occurs. In our context, relocation of supplies can be considered repositioning rather than prepositioning. However we adopt the term prepositioning as the supplies are positioned prior to the occurrence of the disaster event. 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 the number of people who cannot be served post-disaster. In addition, we address the uncertainty in the location of the disaster using short-term forecasts such as those available prior to hurricanes.

This paper makes the following contributions to the literature. The problem we consider is in the preparedness domain (vs. post-response). To the best of our knowledge, this is the first paper in the preparedness domain to consider inventory coordination in emergency planning. Secondly, we consider uncertain supply as well as uncertain demand. It should also be noted that the majority of papers consider historical information to determine where to preposition supplies. In contrast, we consider short-term forecasts to determine where to preposition supplies so as to prevent damage to supplies, while also considering timely service to those affected by the disaster. Lastly, we examine the impact of coordination in the network to provide improved response post-disaster. The coordination decisions considered determine (1) how much supply from external suppliers to preposition, (2) how much local (internal) supply to reposition, and (3) where the external/internal prepositioning activity should take place in the network. Since the first 72 h following a disaster are critical (Salmeron and Apte, 2010), coordination is characterized as a function of the response time and average fill rate. Lastly, we explore the impact of the coordination decisions from a cost and service perspective.

The remainder of the paper is organized as follows. In Section 2 a review of related literature is presented. The model and assumptions are presented in Section 3. Section 4 outlines the numerical study considered in this work, including the specific research questions that are addressed and assumptions made regarding the data used. Computational results are reported in Section 5, followed by concluding remarks in Section 6.

2. Literature review

Much of the prepositioning literature addresses stock levels for relief supplies, location of relief supplies, and/or distribution of relief supplies. Inventory stocking and location decisions are typically implemented in advance of the emergency event, and often reflect long term strategic resource allocation decisions. Distribution of relief supplies happen during the response phase after event demand has been realized and reflects short term resource allocation decisions. Several prepositioning models integrate both preparedness and response decisions using scenario-based approaches such as stochastic programming. The following discussion of the relevant prepositioning literature is classified by the preposition decision. Specific aspects of the model relating to supply and demand uncertainty and the planning horizon are highlighted, where applicable. Short term resource allocation models in the context of humanitarian relief are also discussed.

2.1. Location determination

Many of the location determination models used in the humanitarian relief context are modeled as extensions of the well known facility location models which are adapted to consider uncertainty in demand induced by disaster events. Jia et al. (2007) develop models to determine the location of medical services during large scale emergencies under various objectives: (i) maximize the demand covered by a certain number of facilities, (ii) minimize the demand weighted distance between the new facilities and the demand points, and (iii) minimize the maximum service distance. Both proactive (strategic) facility location decisions and reactive (short term) location decisions are considered. The proactive location case determines where facilities should be located for long term storage of medical supplies such that they can be delivered quickly to demand points, if a terrorist attack occurs. The reactive location case determines where staging centers should be positioned to receive and distribute medical supplies from strategic inventory stockpile locations. Uncertainty in demand is a function of the population covered by a demand point and the impact the attack scenario is likely to have on the demand point. Ukkusuri and Yushimito (2008) also model the supply prepositioning problem as a facility location problem, incorporating routing as well as location decisions. They consider a network location model where existing demand points are considered as candidate locations to preposition supplies, taking into account that possible disruptions in the transportation network can occur via node or link failures. The objective is to choose the locations and routes in such a way that the reliability of reaching a demand point is maximized. *Demand surge* and *supply quantities* are not considered in this model. Yi and Ozdamar (2007) also consider preposition location and routing decisions. They present a multi-period capacitated location-routing problem that incorporates multiple commodities, different categories of wounded victims, selection of temporary emergency sites that can be established in the affected area, and a set of available hospitals that can provide care for victims. The objective is to coordinate transportation of commodities from major supply centers to distribution centers in affected areas, as well as transport the wounded to temporary and permanent emergency units. The optimal locations and transportation routes minimize the delay in providing prioritized service for commodities and health care. More specifically, the weighted sum of unsatisfied demand over all commodities and the weighted sum of wounded people waiting for service is minimized.

2.2. Location and inventory quantity determination

The optimal location and stocking quantities for relief supplies has been considered by a number of researchers. Duran et al. (2011) approach this problem using a mixed integer programming formulation. The objective is to minimize the average response time required to transport items from selected preposition warehouses or global suppliers to a regional demand location. The best decision is weighed against a set of likely demand scenarios that an international relief organization may face. Balcik and Beamon (2008) approach this problem using a scenario-based mathematical model that is a variant of the maximal covering location problem. The number and location of the distribution centers and the amount of relief inventory to stock is determined such that the total expected demand covered by the distribution centers is maximized. The model considers multiple commodities, priority levels associated with commodities, response time requirements for commodities, and budget constraints on prepositioning and distribution activities. Ample supply is assumed to be available to support prepositioning activity. Disaster scenarios are based on worldwide earthquakes and demand is estimated based on the population residing in the affected area. Rawls and Turnquist (2010) also consider distribution, location and inventory stocking decisions. The context for their work is based on hurricane scenarios faced by the gulf coast of the United States. A mixed-integer stochastic programming model is developed that incorporates multiple commodities, possibility of damage to roads, and damage to prepositioned warehouses and thus supplies. The optimal preposition strategy is considered from a cost-based perspective that incorporates (i) the fixed cost of opening a facility and variable purchase cost for commodities; (ii) expected transportation cost associated with distribution of relief supplies to the affected area (post-disaster), penalty for unmet demand and inventory holding costs for unused supply (post-disaster). It is assumed that relief supplies are purchased from an unspecified source with ample quantity. Hurricane scenarios (demand estimates and network damage) are constructed using historical information from past storms. Salmeron and Apte (2010) address the relief needs of an affected population through a prepositioning strategy that involves location, capacity expansion, and resource quantity determination decisions. The affected population is partitioned into three categories: critical population, stay-back population and transfer population. The critical population requires emergency medical evacuation to relief locations. The stay-back population requires delivery of certain commodities from relief locations. The transfer population requires evacuation to relief locations due to short-term displacement. A multi-objective stochastic programming model is developed where the first objective minimizes the total casualties from the critical population and the stay back population. The second objective minimizes unmet demand for the transfer population. The model incorporates parameters to reflect the health deterioration of individuals from the critical population who are not evacuated, budgetary constraints on expansion decisions, and a percentage of the stay-back population that will perish if not supplied with commodities. Decisions made in advance of the disaster (strategic) are location and capacity expansion of relief location assets, expansion of ramp space in the affected areas, prepositioning of additional health workers at relief locations, warehouse expansion for commodities at relief locations, and location of shelters for the displaced. Second stage decisions consider ramp size and transportation needs (size of vehicle fleet) to move the critical population as well as deliver commodities to the stay back population. This model does not explicitly consider acquisition of supplies from local or outside suppliers.

2.3. Short term resource allocation models

A few models exclusively address allocation of relief resources over short term planning horizons. Lodree and Taskin (2009) address the problem of supply planning for retail firms facing demand surges caused by hurricanes. It is assumed that the level of the demand surge can be predicted using wind speed forecast updates. The model is developed as an optimal stopping problem that determines the optimal stocking quantity and the number of observations (forecast updates) to sample. The optimal ordering and sampling policy minimizes the expected order, holding, and shortage costs associated with hurricane induced demand. Taskin and Lodree (2011) extend the prior work to consider multiple retailers and include a wind speed prediction model used by the National Hurricane Center to estimate location specific storm intensity. Taskin and Lodree (2010) develop a multi-period stochastic programming model that addressing production planning decisions for a single manufacturer during the pre-hurricane season planning horizon. Demand for items is a function of the predicted hurricane landfall counts for the upcoming season and hurricane landfall count rate probabilities are determined from a Markov chain model. Rawls and Turnquist (2012) extend their prior work to consider prepositioning supply to satisfy short-term (within 72 h of evacuation order) shelter demand. A multi-period stochastic programming model is presented where the first stage decisions determine where and how many relief supplies to stock; the second stage decisions address how the supply should be distributed over the 72 h period. The model incorporates constraints on shipment of available supply by (i) location specific vehicle loading and dispatching rates, (ii) delivery lags based on distance between storage and demand locations, and (iii) reduced transportation capacity as a result of damaged or destroyed transportation links. The optimal preposition strategy minimizes the expected costs associated with selection of facility sizes and locations, relief supply stocking decisions, unmet demand penalties and distribution of supply to shelter locations.

Sheu (2007) considers an emergency distribution network consisting of multiple suppliers and relief distribution centers capable of responding to the needs of the affected population immediately after an event. A time varying forecast for demand is proposed and integrated within a comprehensive emergency distribution framework. A fuzzy clustering approach is used to group demand areas and accounts for urgency of demand determined. A multi-objective model is used to determine the distribution of relief supply to the affected groups. The 2 objectives considered are maximizing fill rate and minimizing transportation costs. Lastly, distribution of supply to the distribution centers is performed accounting for the urgency associated with the distribution center. The objective is to minimize the weighted transportation costs.

2.4. Research contribution

In the preceding discussion, several stochastic programming models have been proposed to address prepositioning decisions, particularly when both preparedness and response decisions are considered. The reader is referred to Birge and Louveaux (1997) and Higle (2005) for a more comprehensive discussion on stochastic programming models. Our model also uses this approach.

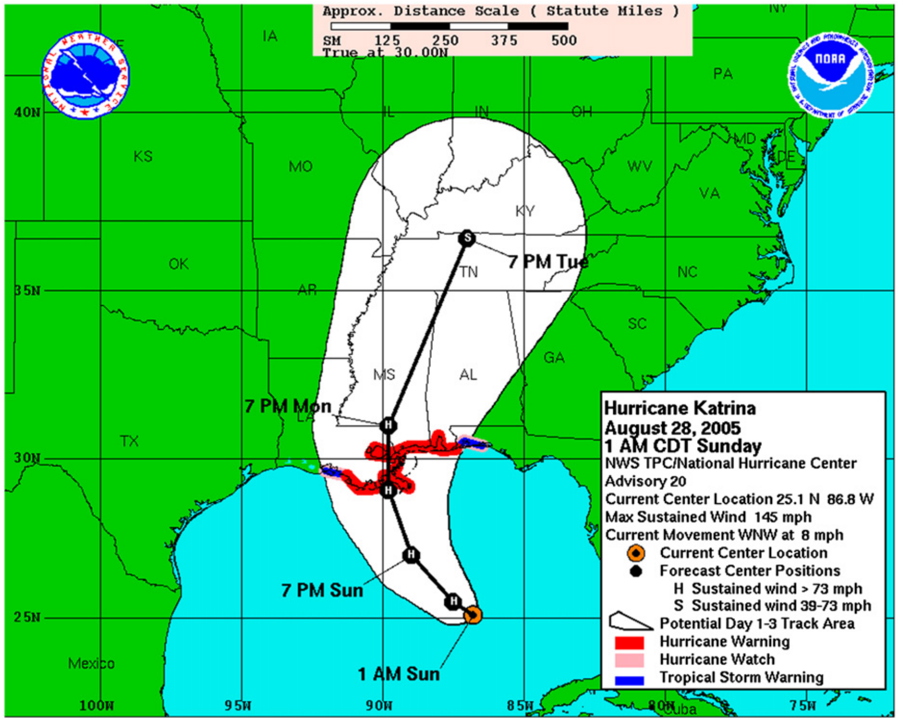

Fig. 1. Tropical cyclone forecast cone for Hurricane Katrina.

The specific decisions addressed in the model are the placement of commodities within a network, and distribution of supplies. Furthermore, we assume there is a finite level of supply available in the network as opposed to considering prepositioning via supply purchases. This allows us to address coordination aspects within the relief network. Our model also explores how short term forecasts can be used to drive operational-level decisions as opposed to using historical season-level forecasts many have used at a tactical level. Much of the work that has been done in prepositioning that uses short term hurricane forecast information has primarily been done by Lodree and Taskin (2009, 2010) for manufacturing firms using forecasted wind speeds in a multi-period framework to determine the appropriate time to order hurricane supplies. In our model, we use storm intensity and error associated with the forecasted storm center (size) to geographically approximate the area that will be affected by the storm.

3. Problem definition

3.1. Background and assumptions

When a storm occurs, meteorologists provide information to the public regarding the likely path, intensity and expected time to landfall. This information is based on several forecast models used by the National Hurricane Center (NOAA, 2009). One particular way this information is conveyed to the public is via the tropical cyclone track forecast cone. The tropical cyclone track forecast cone is a graphical depiction of the current position of the hurricane's center along with the forecasted position over the next 5 days (Fig. 1). It is one of several products produced by the National Hurricane Center. The size of the forecast cone is measured in nautical miles and is based on historical forecast error over the past five years. This particular type of product is typically used by a weather forecaster to provide the viewing audience some information about the likely path of the storm. It is possible for storm effects to be experienced outside of the forecast cone; however it still provides a reasonable approximation for determining the area likely to be affected by the storm.

In the context of the problem under study, this particular product drives the determination of the affected area and likely demand surge experienced as a result of the storm. Certain warehouses within a cooperative distribution network, as well as the surrounding counties supported by supplies within these warehouses, are in the predicted path of the storm. The affected counties and warehouses are determined based on the forecast cone (i.e., the probable track of the hurricane) generated at a specific point in time by the National Hurricane Center. Based on the size and position of the cone over the 5 day period, the supply and demand nodes that lie within the cone can be determined. The details of this particular approach will be explained in a subsequent section of the paper.

Since this particular product is a point in time forecast and is frequently updated, it is important to determine when preparatory actions should be taken. An issuance for a hurricane watch is a natural trigger for taking preparatory actions. As defined by the NHC, hurricane watches are issued for a specific area when tropical storm force winds are predicted to make landfall within 48 h. It is noted that "outside preparedness activities become difficult once winds reach tropical storm force" (NHC, 2012a). Therefore, the hurricane watch serves as the trigger to start the decision making process in this study. There may still be uncertainty about the category at landfall as well as the direction the storm will travel in the next 48 h. However, we assume 48 h is the maximum time available for taking preparatory actions.

As a result of the tropical cyclone forecast, the warehouse network can be partitioned into affected and non-affected sets (i.e., those warehouses that the forecast indicates will be within the cone and are likely to be affected by the hurricane, and those that lie outside of the storm's predicted path). The capability of any warehouse outside of the affected area to provide aid is characterized by 2 parameters: reserve capacity and maximum amount of inventory available to be shipped to the affected area. The reserve capacity can essentially facilitate the transshipment of commodities from affected warehouses to disaster sites after the hurricane. Warehouses in the affected area are characterized by two parameters: initial inventory and capacity. The initial level of inventory is used to satisfy demand due to normal operations. This can be attributed to warehouses that are used to serve a dual role/need in the community. More specifically, there is a normal flow of supplies into these areas when there is no storm which is a function of the population served in the area. This particular scenario is more likely when Food Bank warehouses serve as points of distribution in the community during non-disaster and disaster situations. After the storm event has passed, the inventory that is undamaged is subsequently used in the response effort to satisfy the demand requirements of the affected population.

A percentage of the population will evacuate to shelters, thus creating additional demand for supplies outside of the normal warehouse operating conditions. We assume shelters are located in counties and thus demand is aggregated to the county level. The level of demand is affected by the nature of the event and is thus different from the expected demand during normal operations.

The basic assumptions of the problem described are representative of what may be experienced by a relief organization such as Feeding America, consisting of a network of food banks which satisfy needs of the community daily and during disasters. We formalize the problem assumptions as follows.

We consider a supply and demand network, where each supply node corresponds to a facility such as a warehouse or distribution center with the purpose of holding large amounts of supplies. These supply nodes can be categorized into affected nodes (set A) that fall within the forecast cone and non-affected nodes (set N) that fall outside it. The set of all supply nodes is denoted by $N^+ = N \cup A$. The set of all demand nodes is denoted by H.

Prior to the event, an initial demand forecast for items supplied by the facilities is known and reflects an estimate of the population that is served at a demand location. After an event, the actual quantity demanded may increase if nearby and displaced residents require supplies, decrease if residents of an area are displaced to other areas or stay the same if an area is largely unaffected. This change is determined by what we call a *demand changing factor*, which is a function of the initial demand forecast and the proximity of the demand node to the forecast cone.

Similarly, in the event that the warehouse location is affected by the event, the supply at a supply node may decrease due to facility damage. This change in supply is determined by a *supply changing factor* which is a function of the event severity and the supply node's proximity to the forecast cone.

Interconnections between the supply nodes represent physical transportation routes between facilities such as interstate or state highways. These connections are utilized in both the prepositioning and response stages of the model. Usually each of these arcs will also have capacity limitations. In this model, a specific limit on an arc is not considered. Instead, we consider a congestion factor to represent decreased levels of transportation service (slower travel time between nodes) during the response phase resulting from damaged roadways.

We assume the decision maker has some foreknowledge about the event and takes 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.

3.2. Formulation

We develop a two-stage recourse model where the first-stage decision corresponds to the prepositioning decision and is made prior to the event. This first stage incorporates information obtained from forecast data prior to the event (e.g., the forecast cone obtained 48 h before landfall). The second-stage decision is made after the event has been realized and is referred to as the response phase. 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 Quantity of supplies at supply node n, $n \in N^+$ after supply reallocation
- x_{nj} Quantity of supply units shipped from supply node n to supply node j, $n \in N^+$, $j \in N$
- z_n Unutilized capacity at supply node n, $n \in N^+$
- a_{nj} 1 if any supply is shipped from supply node n to supply node j; 0 otherwise $n \in N^+$, $j \in N$

Second-stage Decision Variables:

- $u_{h\omega}$ Unmet demand quantity at node h, per scenario ω, $h \in H$
- $w_{jn\omega}$ Quantity of supplies shipped from supplier j to supplier n, per scenario ω, $n \in N^+$
- $y_{nh\omega}$ Quantity of supplies shipped from supplier node n to demand node h, per scenario ω, $n \in N^+$, $h \in H$
- $b_{nh\omega}$ 1 if any supply is shipped from supply node n to demand node h per scenario ω; 0 otherwise

Supply node parameters

- I_n Initial inventory stored at supply node n, $n \in N^+$ before supply reallocation
- C_n Storage capacity ($n \in A$)/ Reserve capacity ($n \in N$) at supply node n, $n \in N^+$
- c_p Penalty cost for damaged supplies.
- d^s_{nj} Distance in miles from supply node n to supply node j, n, $j \in N^+$
- T_1 Maximum time allowed for prepositioning in the first stage
- K_1 Congestion factor (in miles per hour) used to approximate travel speed

Demand node parameters

- F_h Forecasted demand at demand node h prior to the event, $h \in H$
- v_h Unit cost for unmet demand at demand node h, $h \in H$
- d^d_{nh} Distance in miles from supply node n to demand node h, $n \in N^+$, $h \in H$
- $m_{h\omega}$ Fraction of demand that must be satisfied
- T_2 Maximum time allowed for response in the second stage
- $K_{2\omega}$ Scenario specific congestion factor (in miles per hour) used to approximate travel speed

Supply and demand changing factors:

- $R_{n\omega}$ Supply changing factor at supply node n per scenario ω, $n \in N^+$ with $0 \le Rn\omega \le 1$.
- $\gamma_{h\omega}$ Demand changing factor at demand node h per scenario ω, $h \in H$

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

$$\min Z = \sum_{n \in N^+} \sum_{j \in N^+} x_{nj} d^s_{nj} + \sum_{\omega \in \Omega} p_\omega \left\{ \sum_{n \in N^+} \sum_{h \in H} y_{nh\omega} d^d_{nh} + \sum_{n \in N^+} \sum_{j \in N^+} w_{nj\omega} d^s_{nj} + \sum_{h \in H} u_{h\omega} v_h + \sum_{n \in N^+} S_n (1 - R_{n\omega}) c_p \right\} \tag{1}$$

s.t.

$$\sum_{j \in N} x_{nj} + S_n = \sum_{j \in N} x_{jn} + I_n \quad \forall n \in N^+ \tag{2}$$

$$\sum_{j \in N} x_{nj} \le I_n \quad \forall n \in N^+ \tag{3}$$

$$S_n + z_n = C_n \quad \forall n \in N^+ \tag{4}$$

$$a_{nj} d^s_{nj} \le T_1 K_1 \quad \forall n,j \in N^+ \tag{5}$$

$$x_{nj} \le I_n a_{nj} \quad \forall n \in N^+, \quad j \in N \tag{6}$$

$$\sum_{j \in N^+} w_{nj\omega} + \sum_{h \in H} y_{nh\omega} \le S_n R_{n\omega} + \sum_{i \in N^+} w_{in\omega} \quad \forall n \in N^+, \omega \epsilon \Omega \tag{7}$$

$$\sum_{n \in N^+} y_{nh\omega} + u_{h\omega} = F_h \gamma_{h\omega} \quad \forall h \in H, \omega \epsilon \Omega \tag{8}$$

$$\sum_{n \in N^+} y_{nh\omega} \ge m_{h\omega} F_h \gamma_{h\omega} \quad \forall h \in H, \omega \epsilon \Omega \tag{9}$$

$$b_{nh\omega} d^d_{nh} \le T_2 K_{2\omega} \quad \forall n,j \in N^+, \omega \in \Omega \tag{10}$$

$$y_{nh\omega} \le S_n R_{n\omega} b_{nh\omega} \quad \forall n,j \in N^+, \omega \in \Omega \tag{11}$$

$$x_{nj}, z_n, w_{nj\omega}, y_{nh\omega}, u_{h\omega}, S_n \ge 0 \quad \forall n,j \in N^+, h \in H, \omega \in \Omega \tag{12}$$

$$a_{nj}, b_{nh\omega} \in \{0,1\} \quad \forall n,j \in N^+, h \in H, \omega \in \Omega \tag{13}$$

In the objective function (1), the first term captures the first-stage cost associated with prepositioning 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 prepositioned supply loss cost. It should be noted that per unit transportation cost is assumed to be a linear function of the distance between two nodes. Minimizing the expected 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 preposition supplies to safer locations are constrained by flow balance Eq. (2) where the summation of the outbound flows and prepositioned supply quantity equals the summation of the inbound flows and initial inventory. Constraints (3) ensure that only the currently available inventory can be repositioned, thus eliminating the possibility of transshipments. Constraints (4) guarantee that the prepositioned supply does not exceed the available storage capacity of the facility. Constraints (5) and (6) ensure the amount of time taken to preposition supplies in the network does not exceed the available time remaining before the storm hits. The second-stage flow balance constraints (7) are modeled in a similar manner to the first-stage flow balance constraints with a larger network now including supplier to supplier ($w_{nj\omega}$, $w_{in\omega}$) and supplier to demand shipments ($y_{nh\omega}$). Constraints (8) capture the supply and demand requirements. Constraints (9) ensure a minimum fraction of demand is satisfied at all demand nodes. Constraints (10) and (11) reflect the permissible time associated with providing response into the affected area, and is influenced by the travel congestion in the network. Finally, we include the typical non-negativity constraints (12) on all decision variables, along with definition of the binary variables (13). The formulation is a stochastic mixed integer linear programming problem. An optimal solution can be found for this problem using appropriate optimization software.

4. Experimental design

4.1. Background and scope

The experimental design is constructed around a core set of research questions which would be helpful in understanding the tradeoffs between coordination, prepositioning, and response.

1. When there is no coordination in the network, what is the fraction of demand that can be met during the response phase?
2. How much additional supply is needed to ensure 100% of the demand is met within the first 48 h? More generically, how much inventory must be available at non-affected warehouses to ensure that *X*% of demand can be satisfied within *Y* days of the event?
3. When the decision maker has the opportunity to influence coordination decisions, how does the best coordinated decision look like (i.e. where should the warehouses be and how much inventory should be placed there)?

Our secondary area of interest will be to quantify the benefit of preposition in terms of cost and unmet demand quantity as well as understand the sensitivity of the solution with respect to the reserve capacity and available supply within the network.

In order to quantify the results of the work and formally define the scope of the experiments we introduce the following definitions.

Definition 1. *Total demand worst case* is defined as $TD_{wc} = \max_\omega\{\Sigma_h m_{h\omega} F_h \gamma_{h\omega}\}$. This value represents the largest scenario-specific total demand. It can equivalently be referred to as the largest demand surge in the network.

Definition 2. *Total demand best case* (no demand surge) is defined as $TD_{bc} = \min_\omega\{\Sigma_h m_{h\omega} F_h \gamma_{h\omega}\}$. This expression reflects the smallest scenario specific total demand.

Definition 3. *Total supply worst case* (experience supply loss) is defined as $TS_{wc} = \min_\omega\{\Sigma_h S_n R_{n\omega}\}$. The value of the supply available for satisfying demand after the event, corresponds to the case where the supply loss is the highest (i.e. available supply is the lowest).

Definition 4. *Total supply best case* (experience no supply loss) is defined as $TS_{bc} = \max_\omega\{\Sigma_h S_n R_{n\omega}\}$. In this case, there is no supply loss and therefore the supply available to satisfy the demand corresponds to the case with the largest scenario-specific total supply.

Definition 5. *No Coordination* is defined as follows: $I_n = 0$, $C_n = 0$ $\forall n \in N$. This implies there is no reserve capacity or no inventory for relief operations at the non-affected warehouses.

Definition 6. *Limited Coordination* is defined as follows: $I_n = 0$, $C_n > 0 \, \forall n \in N$. This implies there is no inventory available at non-affected warehouses to support relief operations. However, there is capacity to accept incoming supply from affected warehouses.

Definition 7. *Demand equity* is defined as follows: $m_{h\omega} = \alpha \; \forall h \in H$, $\alpha \in (0,1]$.

4.2. Model data and scenario generation

The generation of the model data is summarized in five areas: (1) warehouse network, (2) scenario generation, (3) affected area determination, (4) demand estimation for affected area, and (5) initial inventory for affected warehouses.

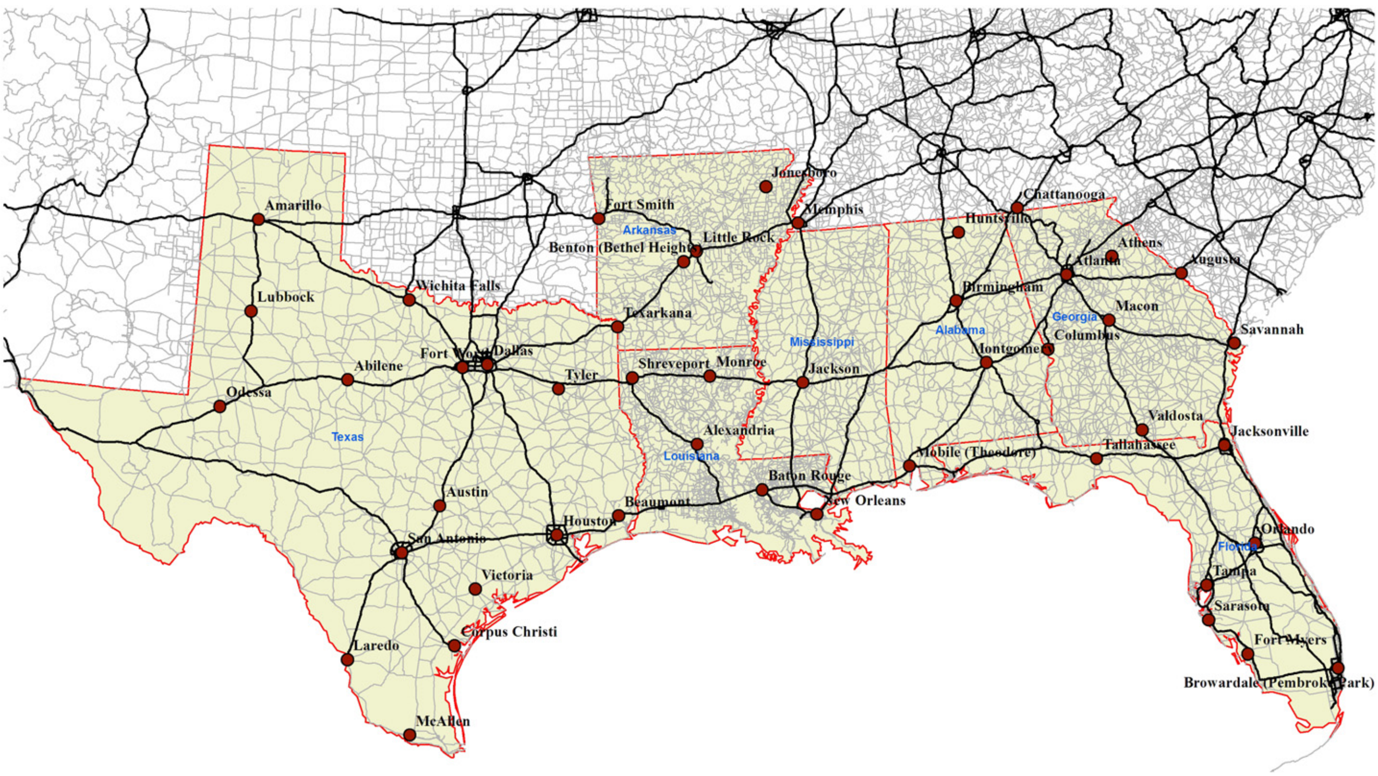

Fig. 2. Supply network.

4.2.1. *Warehouse network*

The warehouse network is based on the southeastern part of the United States and is depicted in Fig. 2. This area is chosen for the numerical study since it is more likely to experience severe storms such as hurricanes. The locations are summarized in Table 1 and were selected using publicly available information about food banks located in the southeastern states. The parishes within the state of Louisiana serve as potential demand nodes. A county level view is appropriate since most counties provide shelters for residents using schools, sports or religious facilities.

4.2.2. *Scenario generation*

There are two levels of uncertainty with respect to the storm: the location of the center and the intensity at landfall. Time-specific forecasts produced by the National Hurricane Center (NHC) are used to represent these two factors. Several hurricane forecast products are generated by NHC as outlined in the NHC product description document (NHC, 2010). However the two operational level forecasts that will drive the development of the scenarios are the tropical cyclone track forecast cone and the maximum one-minute wind speed probability. These forecast advisories are issued every six hours for active cyclones. The forecast cone depicts the current position of the storm center along with the forecasted center position over the next 5 days. The maximum 1-min wind speed probability table provides the likelihood that the tropical cyclone will be in various intensity ranges (according to the Saffir–Simpson scale) over the next 5 days. The size of the forecast cone as well as the probability associated with the various intensity ranges are derived from error statistics based on the forecasted and observed position and intensity from prior years. It is constructed by enclosing the predicted center location by a circle that is set to 2/3 of the official forecast errors over the past 5 years (NHC, 2010). The forecast cone is used to determine the size of the affected area as it characterizes the likely position of the center. Table 2 summarizes the radii of NHC forecast cone circles for each forecast period. Based on this information, at any particular point in time the specific radius of the circle is known and the distance between the forecasted center and location of a demand node can be determined. Therefore, if the distance between a supply node and the forecasted center is less than or equal to the radius, the node is in the forecast cone and thus has the potential to be affected by the hurricane. The reader is referred to the NOAA/NHC (2012b) for more detailed information about this forecast product.

For each tropical cyclone track forecast cone advisory, there is a corresponding maximum wind speed probability forecast. These probabilities are defined across 5 possible intensity outcomes: Tropical Storm/Tropical Depression, Category 1, Category 2, Category 3, Categories 4 and 5. The intensity along with the forecast cone defines 6 possible scenarios as depicted in Fig. 3. For any specific scenario ω, the scenario probability is the product of the probabilities associated with each outcome (relative forecast cone position and intensity).

4.2.3. *Affected area determination*

The affected area is based on the set of warehouses identified in Table 1 and counties within the state of Louisiana. The set of affected warehouses and counties is calculated using the tropical cyclone forecast track at time period t as follows. Let (p_{1t},p_{2t}) represent the forecasted position (longitude and latitude in decimal degrees, respectively) of the hurricane center at time t for a specific advisory, $t \in T = \{12,24,36,48,72,96,120\}$. Let (z_{1h},z_{2h}) represent the longitude and latitude (in decimal degrees) of node h within the supply/demand network. Then the great circle distance in miles between these 2 points is defined by Eq. (14). A node inside this 2/3 probability forecast cone satisfies Eq. (15) where r_t is the radius of the forecast cone circle in nautical miles at forecast period t (refer to Table 2). As a result, any warehouse in this forecast cone has the potential to experience supply loss and

Table 1
Warehouse locations.

City	State
1. Abilene	TX
2. Amarillo	TX
3. Austin	TX
4. Beaumont	TX
5 Corpus Christi	TX
6 Dallas	TX
7 Ft. Worth	TX
8 Houston	TX
9. Laredo	TX
10. Lubbock	TX
11. McAllen	TX
12. Odessa	TX
13. San Antonio	TX
14. Tyler	TX
15. Victoria	TX
16. Wichita Falls	TX
17. Alexandria	LA
18. Baton Rouge	LA
19. Monroe	LA
20. New Orleans	LA
21. Shreveport	LA
22. Jackson	MS
23. Theodore	AL
24. Memphis	TN
25. Ft. Myers	FL
26. Jacksonville	FL
27. Orlando	FL
28. Pembroke Park	FL
29. Sarasota	FL
30. Tallahassee	FL
31. Tampa	FL
32. Bethel Heights	AR
33. Ft. Smith	AR
34. Jonesboro	AR
35. Little Rock	AR
36. Texarkana	AR
37. Athens	GA
38. Atlanta	GA
39. Augusta	GA
40. Columbus	GA
41. Macon	GA
42. Savannah	GA
43. Valdosta	GA
44. Chattanooga	GA
45. Birmingham	AL
46. Huntsville	AL
47. Montgomery	AL

Table 2
Radii of NHC forecast cone circles for 2010, based on error statistics from 2005–2009: (obtained from NHC product description document, 2010).

Forecast period (h) (t)	**2/3 Probability circle, Atlantic Basin (nautical miles)** (r_t)
12	36
24	62
36	85
48	108
72	161
96	220
120	285

any county inside the cone has the potential to experience a demand surge.

$$d_{gc}(t,h) = \left[\cos^{-1}(\sin p_{2t}\sin z_{2h} + \cos p_{2t}\cos z_{2h}\cos(p_{1t} - z_{1h}))\right] \times \left[3963.34 - 13.35\sin\left(\frac{p_{2t} - z_{2h}}{2}\right)\right] \quad (14)$$

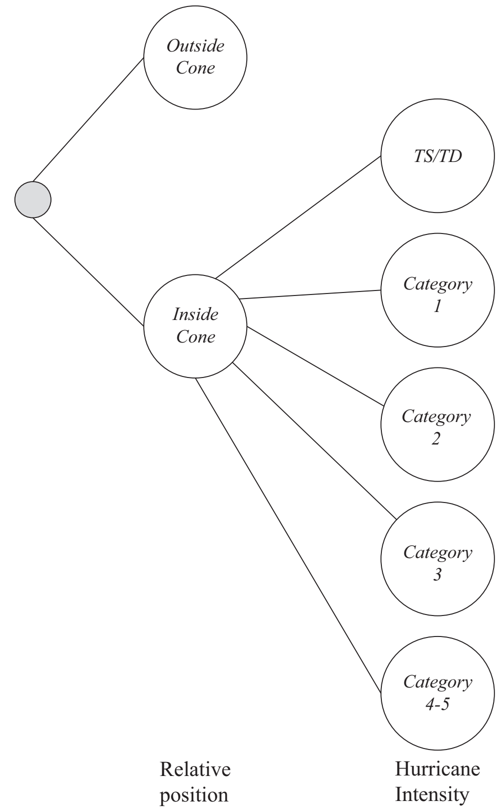

Fig. 3. Scenario structure.

$$d_{gc}(t,h) * 0.868976 \le r_t \quad (15)$$

4.2.4. Demand estimation

The demand for supplies is approximated based on the size of the population within each county in the affected area. It is realistic to assume that some portion of the population would evacuate to a shelter or require some sort of emergency service after the storm depending on the forecasted intensity. Population estimates are obtained from the 2000 Census and provide the basis for estimating the change in demand per scenario. It should be noted that scenario (1) corresponds to the case where the affected counties and warehouses experience no variations in demand or supply respectively.

The change in demand is reflected by the demand changing factor. This factor is calculated as follows.

$$\gamma_{h,\omega} = \left[d'_{gc}(t,h)\right]^{\omega} \quad (16)$$

where $d'_{gc}(t,h)$ is a normalized distance metric for demand node h and $d'_{gc}(t,h) = (\max_{k \in H} d_{gc}(t,k))/d_{gc}(t,h)$ for $\omega \in \{0,1,2,3,4\}$ where 0 denotes the tropical storm/tropical depression case, and 4 corresponds to hurricane categories 4 and 5. For a fixed location, this function is increasing with respect to the hurricane category and ensures that for a fixed category, the demand changing factor is decreasing as the distance increases. As a result, the demand increases as the distance between the county and the forecasted storm center decreases. It should be noted that we bound this value to ensure that the total demand does not exceed the total population in the affected county.

4.2.5. Initial inventory estimation

Initial inventory for warehouses in the affected area is a function of the population in the adjacent counties in addition to the county where the warehouse is located. This is based on the assumption that the adjacent counties make up the primary service area for the affected warehouse. This implies that if a hurricane strikes, each warehouse will (potentially) experience a demand surge. If P_h represents the population in county h, then $I_n = \alpha \Sigma_h 1_n(h) P_h$ where $n \in A$, $1_n(\cdot)$ is an indicator function which equals 1 if county h is adjacent to warehouse n, 0 otherwise, and α is a scaling factor between 0 and 1 to represent the proportion of the population that is served by the affected warehouse.

4.3. Summary of experimental data

Table 3 summarizes the affected warehouses and counties considered for the case study. Initial values for the model parameters are summarized in Table 4. Table 5 summarizes the scenario probabilities. We consider demand equity in the network and therefore set $m_{h\omega}$ to the same value for all demand nodes in a specific scenario. The remaining parameter values that are varied as part of the experimental design are presented in the discussion of the results.

4.4. Performance measures

In addition to the expected cost determined from the objective function of the mathematical model, the following additional performance measures are defined.

$$\text{Average Fill Rate} = \sum_{\omega} p_{\omega} \left[\frac{\Sigma_h \Sigma_n y_{nh\omega}}{\Sigma_h F_h \gamma_{h\omega}} \right] \tag{17}$$

$$\text{Fraction Prepositioned} = \frac{\Sigma_{n \in A} \Sigma_j x_{nj}}{\Sigma_{n \in A} I_n} \tag{18}$$

Eq. (17) determines the average fraction of demand satisfied across all scenarios. We hereafter refer to this quantity as the average fill rate. Eq. (18) determines the fraction of supply in the affected warehouse that is prepositioned.

Table 3
Affected warehouse and counties based on Advisory 17.

Forecast Period	Node type	State	County	Population estimate (in 1000 s) (P_h)
48 h				
	Demand	Louisiana	Assumption	22,874
	Demand	Louisiana	Jefferson[a]	443,342
	Demand	Louisiana	Lafourche	93,682
	Demand	Louisiana	Orleans[a]	354,850
	Demand	Louisiana	Plaquemines[a]	20,942
	Demand	Louisiana	St. Bernard[a]	40,655
	Demand	Louisiana	St. Charles	51,611
	Demand	Louisiana	St. James	21,054
	Demand	Louisiana	St. John The Baptist	47,086
	Demand	Louisiana	St. Mary	50,815
	Demand	Louisiana	St. Tammany[a]	231,495
	Demand	Louisiana	Terrebonne	109,291
Total				1,487,697
Total in service area for warehouse				

[a] Part of service area for warehouse.

Table 4
Data summary.

Parameter	Value
Supply node parameters for affected warehouse	
I_n	$0.2\Sigma_h 1_n(h) P_h$
C_n	$2^* I_n$
$R_{n\omega}$	[1.0,1.0,0.95,0.90,0.85,0.80]
Cost Parameters	
c_p	100
v_h	100
Travel time parameters	
T_1	15
K_1	40
T_2	10
$K_{2\omega}$	[55,50,45,40,35,30]
Demand node parameters	
F_h	$0.2^* P_h$

Table 5
Scenario probabilities.

Advisory – Forecast period	Relative position	Relative position probability	Hurricane intensity	Intensity probability	ω	P_ω
17–48 h	Outside cone	0.33	–	1.00	1	0.33
	Inside cone	0.67	TS/TD	0.0	2	0
			1	0.0	3	0
			2	0.25	4	0.17
			3	0.30	5	0.20
			4 and 5	0.45	6	0.30

5. Results of case study

5.1. Analytical results

Before discussing the results of the computational study, we briefly describe some observations with respect to the model for the single commodity case.

5.1.1. Feasible solution and service

In order for a feasible solution to exist, it must be true that there must be adequate supply (i.e., $TS_{bc} \geq TD_{wc}$). Given the total supply under best case is known and we assume demand equity across all scenarios ($m_{h\omega}$ is the same for all $h \in H$, $\omega \in \Omega$) then the best possible (maximum) fraction of demand that can be filled under the worst case scenario is the ratio of the total supply under the best case to the total unweighted demand under worst case. Formally, this is $(TS_{bc})/\max_\omega\{\Sigma_h F_h \gamma_{h\omega}\}$.

5.1.2. Occurrence of prepositioning

Under the case of limited and no coordination, prepositioning of supplies does not occur if $TS_{wc} \geq TD_{wc}$. This is true since TS_{wc} represents the case where there is maximum supply loss. If the total supply under this condition can satisfy the demand, then the first stage prepositioning costs can be driven to zero by not moving the supplies from the hazardous location to the safe location, provided the expected shortage cost is significantly lower than expected first stage transportation costs.

If $TS_{wc} < TD_{wc} \leq TS_{bc}$, then prepositioning will occur since there exists a solution that can satisfy the demand which requires moving some portion of the supply to safer locations.

5.2. Impact of coordination

Given there is limited coordination and demand equity, the maximum fraction of demand that can be met under the worst case is as follows.

$$m^* = \frac{TS_{bc}}{\max_\omega\{\Sigma_h F_h \gamma_{h\omega}\}}$$

Table 6
Attainable service level by available inventory under limited coordination.

Days of supply available at affected warehouse	C_n for non-affected warehouses	m^*	Expected cost	Fraction prepositioned	# of Warehouses selected	Fill rate
1	360	0.25	$ 63,567.55	0.89	1	0.54
2	360	0.51	$ 86,415.80	0.99	2	0.72
3	360	0.76	$115,770.82	0.96	2	0.84
4	360	1.00*	$138,809.20	0.89	4	1

To examine the impact of coordination, we set $m_{h\omega}=m^*$ for all demand nodes and scenarios where $\omega>1$. Initial inventory in the affected warehouse is defined in terms of days of available supply. In this particular case, the total demand of the population in the service area affected is multiplied by an integer representing the number of days. It is assumed the relationship between supplies needed and supplies consumed is one to one. Table 6 summarizes the relationship between the days of available supply, level of prepositioning, and fraction of demand that is satisfied. It should be noted that even though m^* is a minimum value, when examining service from the perspective of coverage in all scenarios, it can be seen that more than the minimum amount of demand is being satisfied in some nodes.

The primary locations chosen for prepositioning supplies are Louisiana (Alexandria and Baton Rouge), Alabama (Theodore), and Mississippi (Jackson) which are the four closest non-affected warehouses. Baton Rouge and Theodore are the closest and are always selected when only 2 warehouses are chosen for prepositioning. The other 2 warehouses are chosen for the cases were 4 warehouses are selected, with the maximum amount being positioned in the 2 closest warehouses.

When there is no coordination in the network, there is no opportunity to preposition supplies to safer locations. Therefore, the maximum fraction of demand that can be met under the worst case scenario is as follows.

$$m^* = \frac{TS_{wc}}{\max_{\omega}\{\Sigma_h F_h \gamma_{h\omega}\}}$$

Table 7 summarizes the results for this case. Clearly, to achieve 100% demand fulfillment there must be more days of available supply, since the opportunity to limit the potential supply loss through coordination is not an option. However, in comparing Tables 6 and 7, it is noticeable that the expected costs are considerably lower under the case of no coordination. This is due to the fact that a large portion of transportation costs are reduced as a result of carrying extra inventory. This reduction in cost comes at the expense of a lower fill rate. In Table 6, for the scenario when 4 days of supply are available, 66% of the total costs are attributed to first stage prepositioning costs, and 97% of the second stage expected costs are attributed to transportation. However, under no coordination, the first stage costs are 0 and all of the costs are second stage costs with the bulk being attributed to unmet demand. Fig. 4 depicts the cost interaction as a function of the days of available supply under no coordination. The results indicate that even under a situation of possible supply loss, if there is more inventory available, a large fraction of demand can be met in all scenarios. This cost interaction is explored further in Section 5.4.

Table 7
Attainable service level by available inventory under no coordination.

Days of supply available at affected warehouse	m^*	Expected Cost	Fill rate
1	0.20	$ 40,842.01	0.51
2	0.40	$ 32,947.00	0.7
3	0.61	$ 27,013.44	0.85
4	0.81	$ 23,973.03	0.95
5	1.000*	$ 22,591.07	1

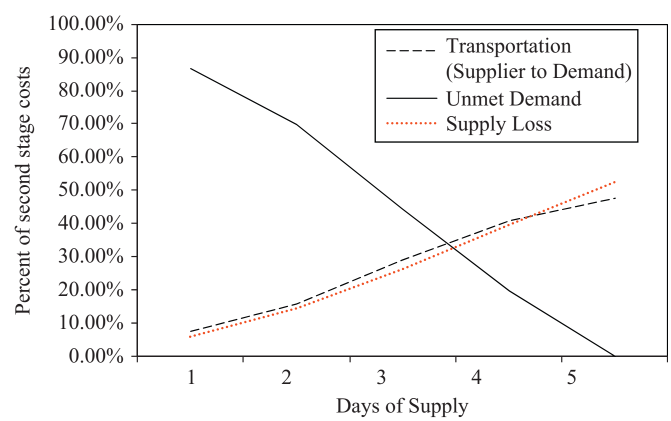

Fig. 4. Second stage cost interaction under no coordination.

Table 8
Impact of travel speed and response time.

Travel speed (mph) in worst case scenario	Response time	Number of warehouses selected	Total inventory positioned in nonaffected warehouse (fraction of worst case demand)	Total cost
20	8	4	0.65	$48,070.01
20	10	5	0.62	$42,396.36
20	12	6	0.59	$41,213.71
30	8	6	0.59	$41,213.71

5.3. Relationship between supply and service

The following explores the relationship between supply (measured in terms of available capacity) and service. Specifically, we address the second question posed in the experimental design in understanding how much capacity must be in the network to ensure 100% of the demand is met at all nodes, across all scenarios, within the first 8 h. To address this with the current model, the initial inventory is changed to a decision variable and a holding cost on inventory is introduced for non-affected warehouses to reflect any costs associated with making inventory available. The initial inventory at the affected warehouse is fixed to reflect 2 days of supply are available (50% service level from Table 6), relative to the affected population. It should be noted that we did not introduce a holding cost parameter in the initial model because it is a sunk cost that would not affect the solution. Fig. 5a–d summarize the results of the model in terms of inventory placement. When capacity is tight, more warehouses are selected and those that are selected are the closest non-affected warehouses, which is intuitively what one would expect. In addition, if the warehouses were rank-ordered in terms of supply, the closest warehouse would have the most supply, followed by the next closest warehouse, and so on. In addition, as more supply becomes available at the affected warehouses, then less supply is needed at the non-affected warehouses. This implies there is an inverse relationship between affected warehouse supply and non-affected warehouse supply. As warehouse supply at the affected warehouse increases, initial inventory at the non-affected warehouse decreases. Furthermore, the presence of initial inventory as a decision variable ensures that the total supply worst case equals the worst case demand. As a result no prepositioning occurs and all demand is satisfied.

Table 8 summarizes the effect of the traffic congestion on the selection of warehouses in the network. Fewer warehouses are selected as the traffic congestion increases (changes from 30 mph to 20 mph). The costs are higher when the desired response time is tight (8 h) because more initial inventory is being made available and immediately distributed to the affected warehouse in the first stage. As a result, overall distribution costs are higher than the other cases listed.

5.4. Sensitivity analysis for economic parameters

The primary economic parameters in the model are associated with transportation of supplies, penalty for unmet demand, and penalty for supply that is not usable (i.e. incurred damage and is therefore considered a loss). In order to characterize the cost behavior in the model, the following cost ratios are defined.

$$r_1 = \frac{c_p}{v}$$

$$r_2 = \frac{c_p}{d^s_{n,j}}$$

$$r_3 = \frac{d^s_{nj}}{v}$$

r_1 represents the ratio of the supply loss cost to unmet demand penalty. r_2 represents the ratio of the supply loss cost to the first stage transportation cost between warehouses. Since the conditions for prepositioning and optimal preposition locations where established in earlier experiments, the results are summarized with reference to the closest non-affected warehouse (Baton Rouge, LA). r_3 represents the ratio of the first stage transportation costs to the unmet demand penalty. Cost ratios are defined relative to the base parameters defined in Table 4. Transportation costs are varied by multiplying the cost parameters by a factor (between 0 and 1) to achieve the desired percentage reduction in cost. For example a 90% reduction in transportation costs is determined as $0.10d^s_{nj}$. Much of the cost interaction is intuitive and is summarized in Figs. 6–8.

If we consider the case with limited coordination, 100% of the demand filled in all scenarios and ensure that the total supply worst case exceeds the total demand worst case, there is no prepositioning unless supply loss costs are extremely high in comparison to first stage transportation costs. Fig. 6 summarizes this behavior for cases when supply loss cost is \$50 ($r_1=0.5$) and \$100 ($r_1=1$) and transportation costs are varied by a factor of 0 to 0.4. The effect of doubling the supply loss cost is evident when $r_3=0$. As r_3 increases, the fraction of supply prepositioned decreases. (It should be noted that as r_3 increases r_2 also increases, but the results are displayed relative to r_3 for consistency). In effect, increasing first stage transportation costs decreases the fraction of supply prepositioned. Therefore, when

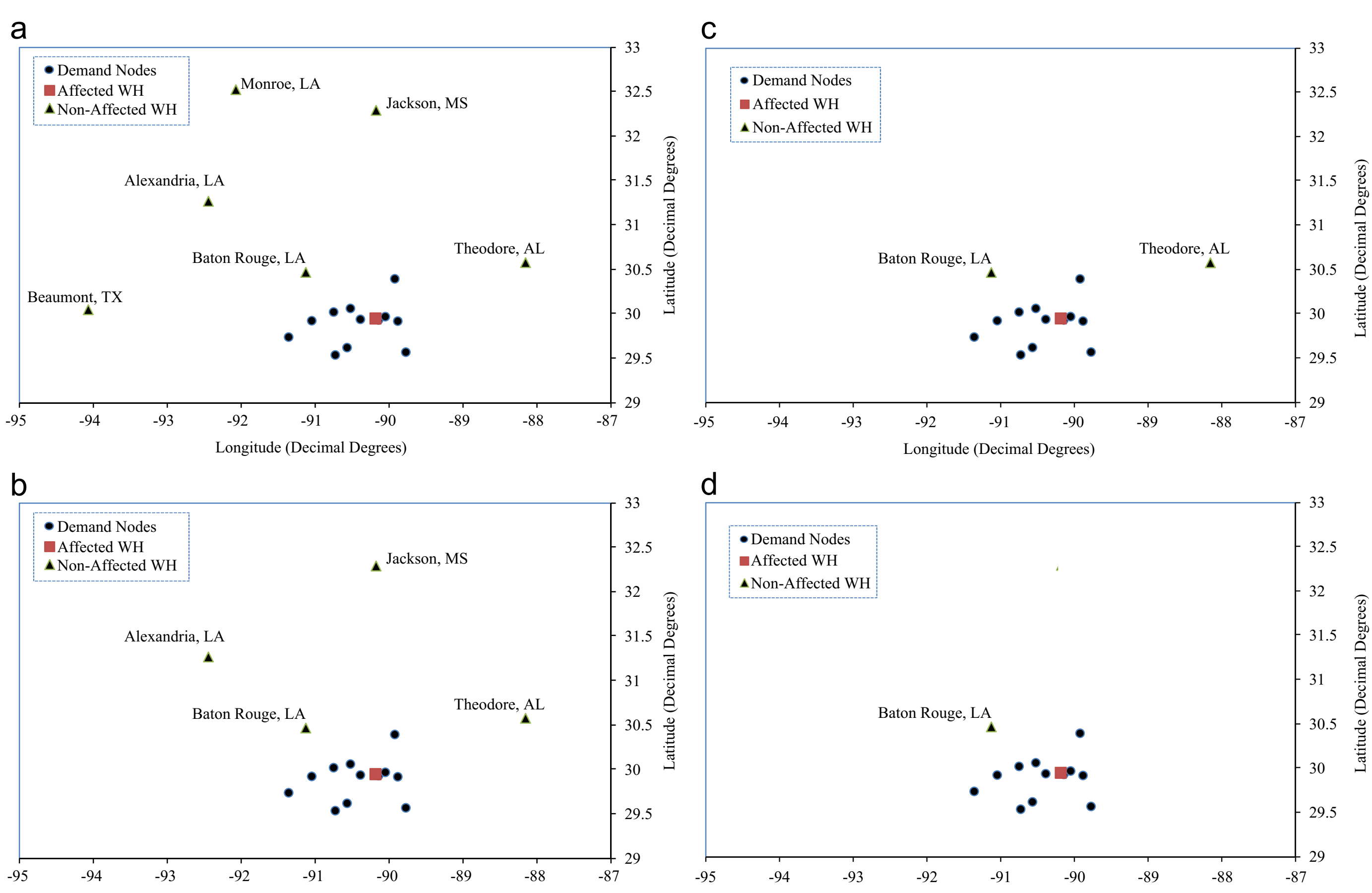

Fig. 5. (a) Capacity=100, days of supply=2; (b) capacity=200, days of supply=2; (c) capacity=300, 400, or 500, days of supply=2 and (d) Capacity=600, days of supply=2.

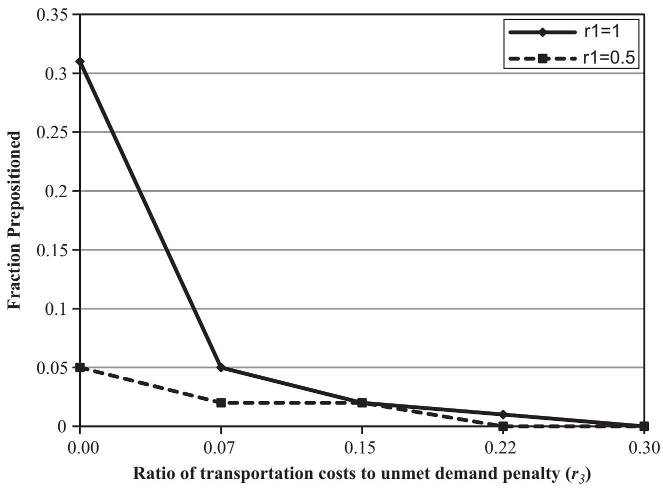

Fig. 6. Fraction of initial supply prepositioned.

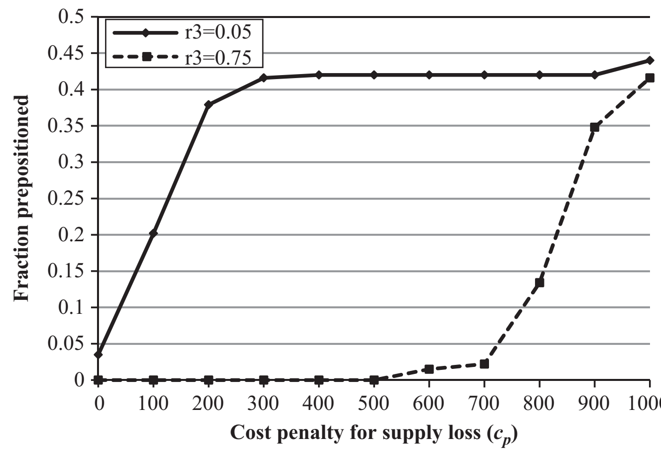

Fig. 8. Fraction prepositioned as a function of the penalty cost interaction.

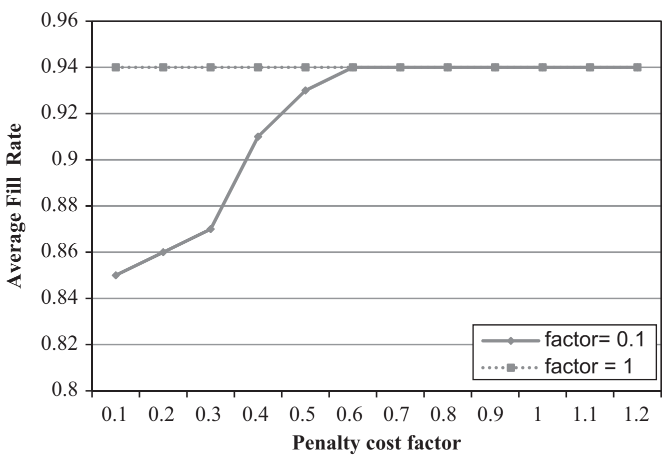

Fig. 7. Average fill rate as a function of changes in the unmet demand penalty.

there is enough supply in the network to satisfy demand in the worst case, it is only beneficial to ensure no supply is lost if transportation costs are relatively small in comparison to the penalty associated with supply loss.

Fig. 7 summarizes the effect of the unmet demand penalty on the fill rate. For this case, the minimum fraction of demand to be met in all hurricane scenarios is 0.5 and the total supply best case exceeds the total demand worst case. Two specific second stage transportation cost factors are considered. The results indicate as penalty costs for unmet demand increase, the average fill rate increases with the closest warehouses being fully satisfied first. In effect, if per unit penalty costs exceed per unit second stage transportation cost for a demand node, then demand is satisfied in its entirety. It is also interesting to note that even though there is enough supply to satisfy demand for all scenarios at 100%, the best possible fill rate achievable is 94%. This occurs because there is supply loss (e.g. no prepositioning) which prevents the demand from the worst case scenario to be fully satisfied at all demand nodes. This is due to the fact that it is not cost effective to send the supply to a safe location and then subsequently distribute from that safe location to demand nodes in the second stage. In this case, it is better to incur some loss rather than achieve 100% fill rate for all scenarios.

Fig. 8 captures the interaction of the penalty costs when transportation costs are kept constant. As the cost penalty for supply loss increases, the fraction prepositioned increases. However, the rate of increase is faster at higher unmet demand penalty costs ($r_3 = 0.05$). Therefore, as the ratio of transportation to penalty costs increase, the fraction prepositioned decreases. However, the percentage decrease is small when the cost penalty for supply loss is very large. Although not displayed in the graph, it should be clear the increasing the fraction prepositioned, reduces supply loss and increases the average fill rate.

6. Conclusions

We have developed a model that illustrates how to perform inventory management coordination in the event of an extreme event such as a hurricane. Our model confirms that the optimal solutions we obtain are intuitive. This is helpful in that a planner's intuition can help guide the repositioning of inventory to safe locations to avoid supply loss. In particular, shelters should coordinate with the closest non-affected warehouses when determining what quantities should be positioned and how those supplies should be distributed to the affected counties based on the desired response time. Our model is helpful in that it can quantify the value of coordination within disaster relief efforts and provides solid backing for this rationale. We characterize the level of service that can be achieved under different coordination mechanisms. In particular, we have identified the amount of relief supply that is necessary to satisfy the needs of the affected population after the event, based on a management determined threshold level.

This model is flexible enough to incorporate effects of non-availability of warehouses as a result of multiple areas being affected by a hurricane, as well as other forms of collaboration. While we have only considered two collaboration cases in the experiment (limited and no coordination), other collaborative mechanisms can be explored by adjusting the capacity and inventory parameters of the non-affected warehouses. The non-affected warehouses could also serve as inventory locations of potential donors and other governmental suppliers. We can also consider multi-state disasters by carefully selecting the affected area based on the forecast path over a 5 day period.

A key challenge of this approach is estimating the demand as a result of the different hurricane scenarios. Better forecasting as it relates to the relationship between demand and hurricane intensity is critical as this determines the optimal solution.

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References

Balcik, B., Beamon, B.M., 2008. Facility location in humanitarian relief. International Journal of Logistics Research and Applications 11 (2), 101–121.
Balcik, B., Beamon, B., Krejci, C., Muramatsu, K., Ramirez, M., 2010. Coordination in humanitarian relief chains: practices, challenges, and opportunities. International Journal of Production Economics 126 (1), 22–34.
Birge, J., Louveaux, F., 1997. Introduction to Stochastic Programming. Spring-Verlag, NY.
Chandes, J., Pache, G., 2010. Investigating humanitarian logistics issues. From operations management to strategic action. Journal of Manufacturing Technology Management 21 (3), 320–340.
Duran, S., Gutierrez, M.A., Keskinocak, P., 2011. Pre-positioning of emergency items worldwide for CARE international. Interfaces 41 (3), 223–237.
Higle, J.L., 2005. Stochastic programming: optimization when uncertainty matters. In: Proceedings of INFORMS, New Orleans, USA.
Jia, H., Ordonez, F., Dessouky, M., 2007. A modeling framework for facility location of medical services for large-scale emergencies. IIE Transactions 39 (1), 41–55.
Johnstone, D.P., Hill, R.R., Moore, J.T., 2004. Mathematically modeling munitions prepositioning and movement. Mathematical and Computer modeling 3, 759–772.
Kaatrud, D.B., Sami, R., Van Wassenhove, L.N., 2003. UN Joint Logistics Center: a coordinated response to common humanitarian logistics concerns. Forced Migration Review, 11–14.
Kovacs, G., Spens, K., 2007. Humanitarian logistics in disaster relief operations. International Journal of Physical Distribution and Logistics Management 37 (2), 99–114.
Lodree, E.J., Taskin, S., 2009. Supply chain planning for hurricane response with wind speed information updates. Computers and Operations Research 36 (1), 2–15.
National Hurricane Center (NHC), 2010. National Hurricane Center product description document: a user's guide to hurricane products. Department of Commerce, National Oceanic and Atmospheric Administration, National Weather Service, National Centers for Environmental Prediction, National Hurricane Center, pp. 1–44.
National Hurricane Center (NHC),2012a. 〈http://www.nhc.noaa.gov/prepare/wwa.php〉 (accessed 12.06.12).
NOAA/NHC, 2012b. 〈http://www.nhc.noaa.gov/〉 (accessed 13.01.12).
NOAA, 2009. Technical summary of the National Hurricane Center Track and intensity models. Available from: 〈http://www.nhc.noaa.gov/pdf/model_summary_20090724.pdf〉.
NRF (National Response Framework), 2008. 〈http://www.fema.gov/emergency/nrf/index.htm〉 (accessed 06.12).
Rawls, C.G., Turnquist, M.A., 2010. Pre-positioning of emergency supplies for disaster response. Transportation Research Part B: Methodological 44 (4), 521–534.
Rawls, C.G., Turnquist, M.A., 2012. Pre-positioning and dynamic delivery planning for short-term response following a natural disaster. Socio-Economic Planning Sciences 46 (1), 46–54.
Salmeron, J., Apte, A., 2010. Stochastic optimization for natural disaster asset prepositioning. Production and Operations Management 19 (5), 561–574.
Sheu, J., 2007. An emergency logistics distribution approach for quick response to urgent relief demand in disasters. Transportation Research Part E: Logistics and Transportation Review 43 (6), 687–709.
SLRC, State Logistics Response Center, Annex-11 Activation protocols. 2012. 〈http://www.floridadisaster.org/Response/Logistics/documents/2009/State%20Logistics%20Plan%20-%20Annex%2011-%20SLRC%20Activation%20Protocols%20Draft.pdf〉 (accessed 06.12).
Stephenson, M., 2005. Making humanitarian relief networks more effective: operational coordination, trust and sense making. Disaster 29 (4), 337–350.
Taskin, S., Lodree, E.J., 2010. Inventory decisions for emergency supplies based on hurricane count predictions. International Journal of Production Economics 126, 66–75.
Taskin, S., Lodree, E.J., 2011. A Bayesian decision model with hurricane forecast updates for emergency supplies inventory management. Journal of the Operational Research Society 62 (6), 1098–1108.
Ukkusuri, S.V., Yushimito, W.F., 2008. Location routing approach for the humanitarian prepositioning problem. Transportation Research Record: Journal of the Transportation Research Board 2089, 18–25.
Van Wassenhove, L., 2006. Blacket memorial lecture humanitarian aid logistics: supply chain management in high gear. Journal of the Operational Research Society 57 (5), 475–489.
Yi, W., Ozdamar, L., 2007. A dynamic logistics coordination model for evacuation and support in disaster response activities. European Journal of Operation Research 179, 1177–1193.