Pre-Positioning of Emergency Items Worldwide for CARE International

Serhan Duran
Department of Industrial Engineering, Middle East Technical University, Ankara, Turkey, sduran@ie.metu.edu.tr

Marco A. Gutierrez, Pınar Keskinocak
H. Milton Stewart School of Industrial and Systems Engineering, Georgia Institute of Technology, Atlanta, Georgia 30332-0205 {marco.gutierrez@gatech.edu, pinar@isye.gatech.edu}

Every year about 500 natural disasters kill around 70,000 and affect more than 200 million people around the world. In the aftermath of such events, large quantities of supplies are needed to provide relief aid to the affected people. There are a number of humanitarian organizations that provide relief aid to survivors of natural and man-made disasters, and CARE International is one of the largest. The most vital issues in responding to such disasters are the agility in mobilizing the supplies and the effectiveness in distributing them. With these objectives, in collaboration with CARE a research group from Georgia Tech developed a model to evaluate the effect of relief items pre-positioning on CARE’s average emergency response time to provide relief aid to people affected by natural disasters. The model’s results helped CARE’s managers to determine a desired configuration for the pre-positioning network.

Key words: pre-positioning; stockpiling; humanitarian logistics; preparedness

1. Introduction

When a disaster strikes, the unavailability of supplies or the slow pace in mobilizing them may cause emergency responses to be ineffective and result in increased human suffering and loss of life. One way in which humanitarian organizations can enhance their emergency response capacity and preparedness to natural disasters and to ensure that there is higher availability of relief supplies is by pre-positioning, or stockpiling inventory. Especially, while responding to sudden onset disasters, natural disasters that occur without a transitional phase such as earthquakes, an established pre-positioning network would be most beneficial by eliminating the procurement phase of the response that will take place after the onset of the disaster otherwise. Nevertheless, structuring a pre-positioning network to support emergency response for sudden onset disasters is not easy because the disasters’ magnitude, timing and location can be highly unpredictable.

There are a number of international relief and humanitarian organizations that provide relief aid to survivors of natural and man-made disasters, and CARE International is one of the largest with programs in more than 65 countries. It was founded in 1945 when 22 American organizations
worked together to provide “care packages” to survivors of World War II. CARE’s mission has evolved since then and today CARE provides emergency relief both during and after disasters and conducts development programs addressing underlying causes of poverty. Although CARE’s main focus is development, emergency relief plays a vital part in its work to create lasting solutions over poverty since many communities in the developing world lack the basic resources to cope with the struggles of everyday life, and when a disaster strikes, that struggle becomes impossible without assistance. Moreover, disasters can drive otherwise self-sustaining communities into poverty erasing years of development.

1.1. CARE’s Approach in Responding to Disasters

In its current practice of responding to a disaster, CARE conducts most of the activities to set up a supply chain to support the emergency response after the onset of the disaster. Some of the major activities include identifying possible suppliers (local and/or international), conducting the procurement process, identifying potential warehouse sites and renting and setting up warehouses. Most of the transportation is outsourced. International suppliers, for example, usually ship the items to an entry port of the affected country by air because of the time sensitivity of demand for relief supplies, and then ship the supplies from the port to a CARE’s warehouse or distribution point by road. The distribution network may take many different forms, but the general characteristic is that CARE relies mostly on third parties for warehousing and transportation because of its lack of infrastructure. The lack of a reliable transportation network and relatively low level of preparedness are common challenges that organizations like CARE face because of the type of funding that they receive. Funding is relatively easy to obtain for a response once a disaster strikes and receives press coverage but is considerably more difficult to obtain for developing infrastructure and preparedness (Murray (2005)).

The source of relief supplies plays an important role in emergency response performance. CARE’s traditional approach has been direct shipments from local and/or international suppliers. Among these two options, organizations like CARE that work toward the dual goals of socio-economic development and relief aid usually prefer local suppliers. Local procurement has the advantage of fast delivery of culturally acceptable products and stimulation of the local economy that may result in a faster recovery of the affected community. However, when procuring locally there may be uncertainties regarding product quality, availability, and production capacity in a disaster’s wake. There is also the risk of inflated prices due to scarcity. When supplies are not available locally, organizations might procure supplies internationally. Procuring items from larger and more reputable international suppliers can increase the availability of higher quality supplies. In addition,
by buying larger volumes from fewer international suppliers, relief organizations can leverage their purchasing power and receive lower prices. The disadvantages are that transportation costs may be higher and the response time slower because of the long distances that have to be traveled from unanticipated sources using unanticipated transportation channels.

In a collaborative project between CARE and Gatech, we explored the third option of pre-positioning for CARE to improve its emergency response times. With such a strategy, relief items would be stored in warehouses in strategic locations around the world and deployed after a disaster hits. Currently, United Nations Humanitarian Response Depot (UNHRD, www.unhrd.org) and some governments are offering free or at cost warehouse storage space and logistics support to international humanitarian organizations such as CARE, therefore the implementation of such a pre-positioning network became feasible. By serving as a complement to the current practice of shipping relief supplies directly from suppliers, a pre-positioning strategy may completely eliminate the procurement phase in some responses and reduce the load on suppliers in others. In addition, relief supplies can be located closer to potential demand locations and transportation arrangements can be made in advance resulting in faster response times and reduced human suffering.

2. Literature Review

The pre-positioning problem falls into the area of humanitarian logistics, which has been formally defined by an advisory committee at the Fritz Institute as “the process of planning, implementing and controlling the efficient, cost-effective flow of and storage of goods and materials as well as related information, from point of origin to point of consumption for the purpose of meeting the end beneficiary’s requirements” (Thomas and Mizushima 2005). Humanitarian logistics is essential to the timely and effective mobilization of resources to aid people made vulnerable by natural disasters and crises. The unpredictable nature of such events, in addition to the large casualties often at stake, make the area of humanitarian logistics a critical aspect of any relief aid operation.

Despite humanitarian logistics’ importance, the literature in this area is limited (Van Wassenhove 2006). Recent disasters such as the 2004 Indian Ocean Tsunami have exposed the challenges and complexities associated with relief aid efforts and have prompted a significant response for the improvement of operations from academics and humanitarian logistics practitioners alike.

There are a number of articles that provide overviews of humanitarian logistics. Alexander (2006) conducts a critical survey of the logistical and organizational components of humanitarian relief. Katoch (2006) examines the conditions that create the distinct, tumultuous atmosphere at a disaster site; the specific characteristics of disasters that make coordination and response difficult;
the instruments used to respond to disasters; and the barriers to effective communication that have developed recently. The Fritz Institute has also released white papers (see Thomas and Kopczak 2005) that outline the nature of disasters and how this nature adversely affects logistical operations.

An important area is the relationship between logistics in the humanitarian and other sectors. Long (1997) discusses the differences between logistics in the industrial (private) and humanitarian sectors. Van Wassenhove (2006) highlights the similarities and differences between industrial and humanitarian logistics, “cross learning” potential between the aforementioned sectors, and the need for greater collaboration between industry, academia and humanitarian organizations for more effective supply chains across the board. Rodman (2004) explores the ways in which an interdisciplinary approach to supply chain coordination—using principles from supply chains in the private, nonprofit, and military sectors—can improve humanitarian operations.

The related academic literature falls into three streams: facility location, inventory management, and network flows. Research in facility location focuses on the spatial aspects of operations and explores the effects of geographical facility location on factors such as cost, service, and response time within the humanitarian relief context. Akkihal (2006) identifies optimal locations for warehousing non-consumable inventories required for the initial deployment of aid. The study solves a p-median problem using historical information on mean annual homeless people resulting from natural disasters as the weights for the different demand locations. As such, the model minimizes the average distance from a forecasted homeless person to her nearest warehouse. The most important underlying assumptions are: (i) every disaster requires a response from a warehouse (its closest warehouse), and (ii) warehouses always have enough inventory to satisfy the demand. Balcik and Beamon (2007) address the issue of pre-positioning relief supplies. They find the optimal warehouse locations and capacities when demand for relief supplies can be met from suppliers and warehouses. Based on historical information, they create scenarios for disaster location and impact (demand) for a single event and minimize the expected response time over all scenarios. Since the set of (location, demand) scenarios consider only single events, the underlying assumption is that warehouse replenishment lead time is zero. But as the actual replenishment time increases, this assumption becomes less valid.

Research in inventory management focuses on estimating item quantities required at various nodes along a supply chain, purchasing quantities, order frequency, and maintenance of safety stock levels. The most recent and relevant works in this category are by Beamon and Kotleba (2006b,a). Beamon and Kotleba (2006b) develops a stochastic inventory control model, in the form of \((Q_1, Q_2, r_1, r_2)\), that determines optimal order quantities and re-order points for a pre-positioned warehouse
responding to a complex humanitarian emergency. In their model, the warehouse supplies items for highly variable demand. They allow for two types of order lot sizes: $Q_1$ for a regular order and $Q_2$ for an urgent order. $Q_1$ is ordered when the inventory reaches level $r_1$ and $Q_2$ is ordered if the inventory level reaches $r_2$ (where $r_1 > r_2$). Beamon and Kotleba (2006a) compares the optimal solution of the $(Q_1, Q_2, r_1, r_2)$ model with a heuristic and a naive inventory model for a pre-positioned warehouse using simulation.

Given the decisions regarding location and replenishment, the next step is the delivery of goods, which can be modeled as a network flow. Haghani and Oh (1996) analyze the transportation of multiple commodities on a network with time windows to minimize loss of life. They formulate a multi-commodity, multi-modal network flow with time windows and present two solution methods. Barbarosoglu and Arda (2004) formulate a similar model but introduce uncertainty. Their model is a two-stage stochastic program over a multi-commodity, multimodal network with uncertainty in demand, in vulnerability of commodity sources, and in survivability of arcs. Barbarosoglu et al. (2002) develop a mathematical model for planning helicopter operations for disaster relief. The model uses operational information to improve tactical decisions in an iterative process. Ozdamar et al. (2004) examine logistics planning in emergency situations involving dispatching commodities to distribution centers of affected areas. Their multi-commodity network flow model addresses a dynamic time-dependent transportation problem, and repetitively derives a solution at given time intervals to represent ongoing aid delivery. The model regenerates plans incorporating new requests for aid material, new supplies and new transportation means that become available during the current planning time horizon.

Our work is most closely related to Balcik and Beamon (2007). Specifically, we find the optimal number and location of pre-positioning warehouses given that demand for relief supplies can be met from both pre-positioned warehouses and suppliers. However, one of the major differences is that we allow multiple events to occur within a replenishment period, thus capturing the adverse effect of warehouse replenishment lead time. Another important difference is that we allow the probability of need for each item to depend on both local conditions and natural hazard type. For example, the probability that a community affected by an earthquake needs hygiene kits is higher than that of a community affected by a flood.

3. Model

To determine the best pre-positioning network configuration for CARE, it is necessary to consider the following:
1. Upfront investment (initial inventory stocking, and warehouse setup).
2. Operating costs (relief items, transportation, and warehouse running cost).
3. Average response time.

We focus on the upfront investment and average response time. Specifically, we try to answer the question: given an initial investment, what is the configuration of the network that minimizes the average response time? At this point we ignore the operating costs because it was not possible to obtain information about CARE’s past responses (cost of supplies and transportation) to estimate a benchmark of operating costs and then compare to an estimate of operating costs with pre-positioning. However, the general idea is that savings may be incurred in procurement and transportation, and additional costs would include the cost of capital of holding relief items in inventory and the warehouse running cost. We expect the warehouse running cost not to be very significant due to government subsidies and collaborations with UNHRD and other humanitarian organizations.

To find the optimal configuration, we used a mixed-integer programming (MIP) inventory location model; the formulation is described in detail in Appendix A. The model considers a set of typical demand instances and given a specified upfront investment (in terms of the maximum number of warehouses and total inventory to allocate) and finds the configuration of the supply network that minimizes the average response time over all the demand instances. We obtained the typical demand instances from historical data, and the supply network consists of the number and the location of warehouses and the quantity and type of items held in inventory in each warehouse.

3.1. Demand

Since the objective of the pre-positioning network is to enhance CARE’s capacity to respond to fast-onset disasters, the model considers only worldwide demand for relief supplies caused by sudden-onset natural disasters. Specifically, we considered the number of people affected by earthquakes, windstorms (hurricanes, cyclones, storms, tornadoes, tropical storms, and typhoons), wave surges (tsunamis and tidal waves), and floods. We disregarded slow-onset disasters such as famine because relief aid providers can prepare in advance to respond to such disasters and provide an effective response without using the pre-positioning network.

To measure past demand for relief supplies, we used historical data from the International Disaster Database (EM-DAT 2007) on the number of affected people affected by natural disasters over the last 10 years. In the database, “affected” is defined as “...[a person] requiring basic survival needs such as food, water, shelter, sanitation ...”. Whereas in a common facility location problem demand can usually be measured (or estimated) directly - such as sales per month - we
took the indirect approach of first measuring the number of affected people and then basing the demand estimate on this statistic because of several reasons. First, CARE does not have accurate records of past responses in terms of quantity and type of items supplied. Second, CARE usually collaborates with other organizations and only provides aid to portions of affected communities. So even if CARE did have accurate records, we would have to consolidate data from numerous organizations. Third, in the past responses relief items might be over or under supplied to assisted communities. Hence, using the indirect approach turns out to be more convenient to estimate total global demand for an organization such as CARE wanting to offer disaster relief aid worldwide.

After collecting data for the number of affected people by different disasters over the past 10 years, we estimated the actual demand quantities for different relief items using the probability of need of different items and the number of items required by an affected person. For the probability of need, we relied on operational guidelines from the International Federation of Red Cross and Red Crescent Societies (IFRC 2000, see also Appendix B). The guidelines, based on field experience, provide the likelihood of different needs of people affected by different disasters. The likelihoods are expressed as “high” potential need, “medium” and “low”. For our calculation, we assigned the probabilities of 0.75, 0.50 and 0.25 to “high”, “medium” and “low”, respectively. To determine the number of items required by a person, we used CARE’s specifications. To illustrate the procedure, consider a hurricane in a hot region of Central America affecting 10,000 people. The IFRC guidelines state that the potential need for emergency shelter in hot weather after a hurricane is “high”, and CARE’s specifications state that one emergency shelter should be provided for 5 people. Therefore, our estimate of the number of emergency shelters required for this response is 1500.

To model the geographic location of the demand points, we aggregated data by geographical regions. We used the United Nations’ (UN) 22 sub-regions as demand point locations. We assume that when a disaster hits one of the countries in a sub-region, the demand associated with the event occurs at the sub-region’s center of population (center of mass). To calculate the centers of population of the different sub-regions, we used data from the Global Rural-Urban Mapping Project (GRUMP 2007). GRUMP’s database contains the geographic location of different human settlements around the world and their size. As a result, the model contains 22 demand points corresponding to all the sub-regions of the world.

The final step in preparing the demand instances was clustering to model the possibility of responses to simultaneous events in different locations. This is important because disasters happening within the warehouse replenishment time must be satisfied by the on-hand inventory across warehouses. Assuming that the replenishment lead time for the pre-positioning warehouses would
be 2 weeks - based on CARE’s expectation of the potential suppliers’ lead time - we grouped historical events that happened within the lead time and obtained 233 demand instances from the data of the last 10 years. Each demand instance consists of demand quantities for the different relief items at one or more demand points.

3.2. Supply

The global suppliers can provide direct shipments for emergency responses and replenish the pre-positioning warehouses. As mentioned previously, emergency responses are usually ad hoc, and humanitarian organizations don’t usually track the performance of the suppliers. As a result, information about the geographic location and average lead time of different suppliers was unavailable for our study. To overcome this problem, the model assumes that there are suppliers for all relief items that can supply items to any demand point in an average time of 2 weeks, considering the time required for the procurement phase and transportation to the affected country. The estimate is based on CARE’s current perceived average response time.

We considered 12 different sites as candidate warehouse locations. As Table 1 illustrates, these include UNHRD locations or where CARE is considering to open a warehouse, possibly in collaboration with other humanitarian organizations. The geographical spread of the possible warehouse locations is illustrated in Figure 1.

<table>
<thead>
<tr>
<th>Table 1</th>
<th>Potential warehouse locations considered by the organizations</th>
</tr>
</thead>
<tbody>
<tr>
<td>Country</td>
<td>UNHRD</td>
</tr>
<tr>
<td>Cambodia</td>
<td>✔️</td>
</tr>
<tr>
<td>China, Hong Kong</td>
<td>✔️</td>
</tr>
<tr>
<td>Denmark</td>
<td>✔️</td>
</tr>
<tr>
<td>Germany</td>
<td>✔️</td>
</tr>
<tr>
<td>Honduras</td>
<td>✔️</td>
</tr>
<tr>
<td>India</td>
<td>✔️</td>
</tr>
<tr>
<td>Italy</td>
<td>✔️</td>
</tr>
<tr>
<td>Kenya</td>
<td>✔️</td>
</tr>
<tr>
<td>Panama</td>
<td>✔️</td>
</tr>
<tr>
<td>South Africa</td>
<td>✔️</td>
</tr>
<tr>
<td>UAE, Dubai</td>
<td>✔️</td>
</tr>
<tr>
<td>USA, Miami</td>
<td>✔️</td>
</tr>
</tbody>
</table>

There are seven relief items identified by CARE to be stored in the pre-positioning warehouses: food, water & sanitation kit, hot weather tent, cold weather tent, household kit and hygiene kit. We consider a pre-set inventory level at each warehouse and that inventory is replenished after each response. The warehouses are replenished by global suppliers and no transshipment activity occurs between warehouses.
3.3. Response Time

The objective function of the MIP model (Appendix A) minimizes the average of the weighted response times over the 233 demand instances (where the weights correspond to the proportion of demand met from the global suppliers and the warehouses). The response time is the time that it takes the initial shipment to arrive at an entry port of the affected country. Hence, for direct shipments from suppliers, the response time is 2 weeks, whereas for the pre-positioning warehouses it depends on the distance between the warehouse and the demand location. Specifically, it is the time that it takes to fly the great arc distance between the points at the speed of a common cargo airplane used in humanitarian relief - the C-130 - plus one day for set-up and material handling at the warehouse.

Other factors such as customs clearing, level of unrest, road damage, socio-political factors and last-mile distribution could impact the response time. However, we focus on international transportation and ignore these factors because their effect would be the same regardless of the pre-positioning network configuration.

3.4. Results

We consider two types of capacity (or budget) constraints: the maximum number of warehouses to open and the maximum inventory amount to keep throughout the pre-positioning network. Both of these constraints (constraints 6 and 7 in the Appendix A) are always binding because the model assumes that demand can be satisfied faster from the pre-positioning warehouses than with direct shipments from the suppliers. We ran the model for 1-9 warehouses to open and for 3 levels of
allowed inventory (high, medium and low). The model decides which warehouses to open and how to allocate the inventory among them. The high, medium and low levels of inventory correspond to 100%, 50% and 25% of the average demand per demand instance, respectively.

We chose to use the number of warehouses and maximum inventory as parameters because CARE often receives in-kind donations in the form of relief supplies and services. For instance, a donor might be interested in donating water sanitation kits or an organization or government might be willing to donate a warehouse and manage it for CARE. This is precisely the case of the UNHRD, which is willing to provide warehousing space for CARE and other organizations in different locations around the world and provide services such as material handling at a cost recovery basis. Therefore, estimating a warehouse setup cost and prices for the initial stocking of supplies was not critical in this context.

We performed all the computations on a 4×900MHz processor using ILOG OPL Studio with the CPLEX solver. The model includes 22 demand points, 12 candidate warehouse locations, 7 relief items and 233 demand instances. As a result, the MIP model includes about 470,000 variables, 12 of which are binary, and about 56,000 constraints. All computation runs reached the optimal solution within four hours. Figure 2 illustrates the results of the 1-9 warehouses and 3 levels of inventory.

![Figure 2](image)

(a) Low Inventory Level  
(b) Medium Inventory Level  
(c) High Inventory Level

**Figure 2**  
Average response times as the number of open warehouses increase

As expected, for a given level of inventory, the average response time decreases as the number of open warehouses increases. Considering that the benchmark response time is 2 weeks (or 336 hours) when no pre-positioning is used, there is a large initial drop in response time as we go from one to two warehouses. Then the average response time decreases at a diminishing rate as the number of warehouses increases reaching a minimal marginal benefit after 3 - 4 warehouses.
Figure 3 illustrates the optimal warehouse locations, when 3 warehouses are allowed, along with their relative allocation of inventory. At the low inventory level roughly 50% of the inventory is held in Southeast Asia (Hong Kong), 35% in the Middle East (Dubai) and 15% in Central America (Panama). As the allowed inventory increases, there is a relative shift of inventory to Southeast Asia until it is so high (69% of inventory held at Hong Kong when inventory level is high) that it can be used to satisfactorily cover demand in South and Central Asia and part of the Middle East, and it is no longer optimal to also open a warehouse in the Middle East (Dubai) but to open it in Africa (in Kenya, with 20% of inventory). For the case of 4 or more warehouses, the optimal warehouse locations do not change with increasing inventory levels. The optimal solution for 4 warehouses includes all of the locations of the optimal solution for 3 warehouses, except for India instead of Dubai. The complete list of locations are given in Table 2.

CARE expects to receive gradual funding from donors for the pre-positioning network, i.e. it does not have the resources to setup 4 or 5 warehouses from the beginning and stockpile millions of dollars worth of relief supplies. As such, it is important to consider the optimal solutions at the different number of warehouses and inventory levels illustrated in Figure 2. It is more reasonable to expect that CARE will receive small funding to start pre-positioning at a single warehouse and then gradually build up the inventory and expand to multiple locations. In such a situation, opening the first warehouse at its optimal location (India) as the first step in the development of a pre-positioning network process can be suboptimal, since the final pre-positioning network may include 3 warehouses depending on the funds availability.
Table 2  Optimal locations for a given number of warehouses for low and medium inventory level. For high inventory level, the only location change is Kenya instead of Dubai when the number of warehouses to open is 3.

<table>
<thead>
<tr>
<th>Locations</th>
<th>Number of Warehouses</th>
</tr>
</thead>
<tbody>
<tr>
<td>Locations</td>
<td>1 2 3 4 5 6 7 8 9</td>
</tr>
<tr>
<td>Cambodia</td>
<td>✓ ✓ ✓ ✓ ✓</td>
</tr>
<tr>
<td>Hong Kong, China</td>
<td>✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓</td>
</tr>
<tr>
<td>Denmark</td>
<td>✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓</td>
</tr>
<tr>
<td>Germany</td>
<td>✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓</td>
</tr>
<tr>
<td>Honduras</td>
<td>✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓</td>
</tr>
<tr>
<td>India</td>
<td>✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓</td>
</tr>
<tr>
<td>Italy</td>
<td>✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓</td>
</tr>
<tr>
<td>Kenya</td>
<td>✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓</td>
</tr>
<tr>
<td>Panama</td>
<td>✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓</td>
</tr>
<tr>
<td>South Africa</td>
<td>✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓</td>
</tr>
<tr>
<td>UAE, Dubai</td>
<td>✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓</td>
</tr>
<tr>
<td>USA, Miami</td>
<td>✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓ ✓</td>
</tr>
</tbody>
</table>

Therefore, our final recommendation to CARE was to open the first warehouse in the Middle East, then expand to Central America and then to Southeast Asia and to aim to roughly allocating 35%, 15% and 50% of the inventory, respectively, among the warehouses when all three are operating. Following this gradual expansion plan, the pre-positioning network would be very close to the optimal configuration at each step as shown in Figure 3 - especially for the low and medium inventory levels, which are more realistic than the high inventory level. If CARE continues expanding the pre-positioning network and opens a fourth warehouse in Africa and even a fifth in Europe, the final configuration would still be very similar to our suggested solution, and thus the performance would be very close to the optimal.

3.5. Sensitivity Analysis
In our computational study, we obtained 233 demand instances from the past 10 years’ disaster history in which a disaster or a group of disasters need to be responded without any replenishment. To test whether the results obtained are robust, we also generated demand scenarios using probability distributions from historical data. First, we calculated frequencies of the disaster types that took place at various locations from the historical data, and used them as the probabilities of different disaster types striking that location. Similarly, we determined the discrete probability distribution of the number of affected people at each demand location by disaster types. Then using simulation techniques (see Appendix C for details), we again created 233 demand instances representing alternative 10-year scenarios.

We did not observe a significant difference between the results when we used the historical
scenario or the scenarios generated using simulation. The locations of the warehouses and the allocation of inventory are very similar across the scenarios we tested (see Appendix C).

4. Conclusion

Emergency supply pre-positioning, as a complement to the current strategy of direct shipments, can have several benefits for CARE. Some of them are more efficient procurement of goods, improvement of response times and freight cost reductions. The last two, particularly, depend at a high degree on the configuration of the pre-positioning network. The results of our model illustrate how to best use upfront investment to achieve the highest possible benefit in both, and also support the implementation of a gradual network expansion strategy. The model estimates the frequency, location and magnitude of potential demand based on historical data and optimizes the location of warehouses and inventory allocation given an upfront investment in terms of number of warehouses to open and amount of inventory to hold.

The model helped CARE determine the desired configuration of the network and provided a roadmap of how to get there as funds become available. By understanding the benefits in performance and overall configuration of the network, CARE can now narrow down their initial options and within each proposed region consider other criteria such as political stability of the candidate location, customs regulations, cost of warehouse, labor skill level, labor cost, logistics accessibility and possibility of collaboration with other organizations to make their final decision.

Based on our recommendation, CARE intends to start pre-positioning emergency supplies in Dubai in collaboration with other organizations as soon as the implementation plans are finalized and funds become available to procure the initial supplies.

Acknowledgments

We would like to thank Rigoberto Giron (Emergency and Humanitarian Assistance Unit Director), John Solomon (Emergency Support Services Advisor), and David Gazashvili (Emergency Preparedness Planning Advisor) from CARE USA for their support, and acknowledge Adaora Okwa’s effort in the early phase of the project.

Appendix A: The Mixed Integer Programming (MIP) Formulation

Index Sets:

- $J$ set of possible pre-positioning warehouses.
- $H$ set of disaster types.
- $I$ set of regional demand locations.
- $L$ set of supply items.
- $K$ set of demand instances need to be responded by the pre-positioning warehouses.
**Variables**

- \( y_j \) \( \begin{cases} 1 & \text{if warehouse } j \text{ is opened,} \\ 0 & \text{otherwise.} \end{cases} \)

- \( q_{j\ell} \) quantity of supply \( \ell \) held at warehouse \( j \).

- \( x_{ijkt} \) quantity of supply \( \ell \) sent to regional demand location \( i \) from warehouse \( j \) in demand instance \( k \).

- \( x_{ik\ell} \) quantity of supply \( \ell \) sent to regional demand location \( i \) from suppliers in demand instance \( k \).

**Parameters**

- \( N \) maximum number of warehouses to open.

- \( Q \) total inventory allowed.

- \( p_k \) probability of demand instance \( k \).

- \( t_{ij} \) response time from warehouse \( j \) to regional demand location \( i \) (flight time).

- \( t_{ij} \) response time from suppliers to regional demand location \( i \) for supply \( \ell \).

- \( d_{isk} \) number of affected people at regional demand location \( i \) by disaster type \( h \) in demand instance \( k \).

- \( p_{h\ell} \) probability of supply \( \ell \) being required at regional demand location \( i \) by a person affected by disaster type \( h \).

- \( a_{h\ell} \) quantity of supply \( \ell \) required by a person affected by disaster type \( h \) in demand location \( i \).

- \( d_{ik\ell} \) expected demand for supply \( \ell \) at regional demand location \( i \) in demand instance \( k \).

Based on the above definitions, we developed the following MIP formulation:

\[
\begin{align*}
\text{min} & \sum_{k \in K} p_k \left[ \sum_{i \in I} \sum_{\ell \in L} x_{ik\ell} t_{i\ell} + \sum_{i \in I} \sum_{j \in J} \sum_{\ell \in L} x_{ijkt} t_{ij} \right] \\
\text{s.t.} & \quad \bar{d}_{ik\ell} = \sum_{h \in H} a_{h\ell} p_{h\ell} d_{hik} \quad i \in I, k \in K, \ell \in L, \\
& \quad \sum_{j \in J} x_{ij\ell} + x_{ik\ell} \geq d_{ik} \quad i \in I, k \in K, \ell \in L, \\
& \quad \sum_{i \in I} x_{ij\ell} \leq q_{j\ell} \quad j \in J, k \in K, \ell \in L, \\
& \quad q_{j\ell} \leq Q y_j \quad j \in J, \ell \in L, \\
& \quad \sum_{j \in J} \sum_{\ell \in L} q_{j\ell} \leq Q, \\
& \quad \sum_{j \in J} y_j \leq N.
\end{align*}
\]

Constraints (2) calculate the expected demand of different supply items given that a number of people are affected by a specific disaster type. Constraints (3) ensure that demand at each regional demand location is completely satisfied from the warehouses and/or the suppliers in each demand instance. Constraints (4) ensure that, for each demand instance, the number of supply items shipped from a warehouse is less than or equal to the inventory held at that warehouse. Constraints (5) only allow opened warehouses to hold inventory. Constraints (6) make sure that the sum of the inventories allocated to the different warehouses is less than or equal to the total inventory (\( Q \)) allowed and constraints (7) ensure that the number of warehouses
opened is less than or equal to $N$. The objective function (1) of this model is to minimize the expected average response time over all the demand instances.

As discussed in Section 3, the computational results are obtained by considering 12 warehouse candidate locations and four disaster types. The warehouses are replenished by global suppliers and a 2 week replenishment lead time is assumed (thus, $t_{ij} = 336$ hrs). Using a 2 week time window in which disasters must be responded without replenishment, from the last 10 years’s historical data, 233 demand instances are created. Each demand instance contains the amount of 7 supplies items needed at the 22 regional demand locations worldwide. We assumed that the probability of any such demand instances is same therefore, $p_k = 1/233$ and can be omitted from the formulation.

Average response time is calculated using the weighted time average of the supply items sent from warehouse locations or global supplier locations. The time to respond from a warehouse location to any regional demand location is calculated as the flight time of the “great arc distance” over the earth between these locations by a C-130 cargo plane.

Appendix B: Operational Guidelines Adapted from IFRC

To calculate the demand for the actual items, we translate the data of the number of affected people into items. Table 3 is adopted from IFRC (2000). It illustrates the likelihood (L,M,H) of need for each item by people affected by different hazards. As an example, emergency shelter (tents); the likelihood of need after earthquakes is generally low but depends on the climate. If it is cold, the likelihood of need increases. For floods, the likelihood of need is lower because the population is not displaced from their homes for a long period of time. This qualitative information with the climate conditions of the demand locations are used to estimate $p_{h,\ell,i}$; probability of supply item $\ell$ being required at regional demand location $i$ by a person affected by a disaster type $h$.

<table>
<thead>
<tr>
<th>Table 3</th>
<th>Potential Emergency Needs</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Water and Sanitation</strong></td>
<td></td>
</tr>
<tr>
<td>Distribution, storage, processing</td>
<td>H</td>
</tr>
<tr>
<td>Personal Hygiene</td>
<td>H</td>
</tr>
<tr>
<td>Insect and rodent control</td>
<td>M</td>
</tr>
<tr>
<td><strong>Food and Nutrition</strong></td>
<td></td>
</tr>
<tr>
<td>Short term distribution</td>
<td>H</td>
</tr>
<tr>
<td>Supplementary curative feeding</td>
<td>L</td>
</tr>
<tr>
<td>Agriculture</td>
<td>L</td>
</tr>
<tr>
<td><strong>Shelter and Household Stock</strong></td>
<td></td>
</tr>
<tr>
<td>Emergency Shelter</td>
<td>L,C</td>
</tr>
<tr>
<td>Fuel for dwellings</td>
<td>L</td>
</tr>
<tr>
<td>Kitchen utensils</td>
<td>H</td>
</tr>
</tbody>
</table>
Appendix C: Results of the Sensitivity Analysis

To create a demand instance, we simply generate a sequence of uniform random numbers; $u_1, \ldots, u_{88}$. Each random number is used to decide if one of the four disaster types take place at one of the 22 demand locations by comparing it to the frequency obtained from history. If a disaster strikes a location, an additional uniform random number is used to decide the number of people affected from the corresponding discrete probability distributions determined. We repeat this process to obtain 233 randomly generated demand instances.

Figure 4 illustrates the optimal location and inventory allocations while responding to 10 generated random scenarios when the inventory level is low. If we compare them with the corresponding results of the demand instances generated from historical data in Figure 3, we see that the inventory allocations are very similar, and the only difference is the location of the Central America warehouse: from Panama to a close proximity location Honduras.

References


