LOCATING POINTS OF DISTRIBUTION IN LARGE URBAN DISASTERS

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ABSTRACT

This paper proposes an approximate mathematical formulation as a planning tool to estimate the number of points of distribution (PODs), their capacities, and the frequency of distribution strategy required for large urban disasters. The formulation is designed to require a minimum set of inputs so that it could be used to rapidly get an idea about a quasi-optimal configuration of the POD network. The quasi-optimal configuration is obtained as the one that minimizes the total social costs defined as the summation of the cost of: (i) locating the PODs, (ii) manning the servers at the PODs, (iii) transporting supplies to the PODs, (iv) walking to the PODs, (v) waiting times at the POD, and (vi) risk costs associated with the distribution strategy. The formulation takes into account the impacts on human suffering through the consideration of the costs of walking, waiting, and security risks. The paper conducts a number of numerical experiments that provide important insight for POD planning.

KEYWORDS: Facility Location; Points of Distribution; Service Capacity; Humanitarian Logistics; Human Suffering
1. INTRODUCTION

In recent years, the experiences from Hurricane Katrina, the Northern Pakistan and Indian Kashmir Earthquake, the Indian Ocean Tsunami, Haiti, Chile and Japan, highlight the importance of logistics to mitigate the humanitarian crises triggered by disasters. A common factor in all these cases has been the overwhelming humanitarian logistics challenge presented to relief organizations to meet the needs of the impacted population (Thomas, 2003; Adinolfi et al., 2005). The heart of the problem is that in large disasters, the needs for life sustaining items increase tremendously as: (1) large portions (and even all) of the supply inventories at households and businesses in the impacted area are destroyed, depriving the population of ready access to critical items; and, (2) commercial supply chains are severely impacted, which delays the supply of resources to affected areas (Holguín-Veras et al., 2012d). As a consequence, there is an urgent need for significant improvements in the efficiency of humanitarian logistics. These improvements are not only to avoid logistical failures ensuring an efficient and reliable flow of critical resources to the disaster area (Holguín-Veras et al., 2007; Jaller, 2011; Holguín-Veras and Jaller, 2012; Holguín-Veras et al., 2012b; Holguín-Veras et al., 2012d), but to guarantee a delivery process that takes into account economic considerations (i.e., transportation, inventory, location costs) and the human side i.e., suffering (Holguín-Veras et al., 2010; Holguín-Veras et al., 2012b; Holguín-Veras et al., 2012c).

Efficient humanitarian logistics necessitates the use of a layered process. An example is outlined by the National Response Plan (U.S. Department of Homeland Security, 2004) where at the top large flows of cargo are moved by a relatively small number of very large distributions centers, while at the bottom the local distribution is handled by a large number of points of distribution (PODs) at which supplies are handed out to the people in need. Although not identified as a research priority, it turns out that the local distribution is the most challenging part of the post-disaster humanitarian logistics (PD-HL) process. The experience in Haiti made that point crystal clear. At the height of the crisis, the massive amount of aid transported to Port au Prince experienced major delays in the distribution to the people in need. The field work done by the authors suggests that the lack of an adequate local distribution network was at the root of the problem (Edmonson, 2010; Holguín-Veras et al., 2010; Holguín-Veras et al., 2012a). In fact, it took the United Nations (UN) about three weeks to setup 14 PODs (New York Times, 2010), clearly an insufficient number given that more than 1.7 million people needed supplies (Office for the Coordination of Humanitarian Affairs, 2011). A similar situation was observed in Japan where—in spite of the fact that it was not covered by the international press—the local distribution was not very efficient (Holguín-Veras et al., 2012d), in the participants’ words: “...transporting to distribution centers was easy...”, while “…transporting to refuge centers was very difficult...” (Holguín-Veras et al., 2011). Consequently, ensuring an appropriate network of PODs is a necessary condition for the success of a PD-HL operation (Holguín-Veras et al., 2010) (Holguín-Veras et al., 2012b). The challenge is that, if the number of PODs is too small or their capacity is not adequate, there would be huge delays, unnecessary human suffering, and possibly a collapse in social order as it happened in both Haiti and Chile. Images of tens of thousands of individuals trying to get food and water at a POD in Port au Prince are an example of what must be avoided (Cole et al., 2010). On the other hand, if the number of PODs or their capacity is too large, resources would be wasted.

However, estimating the optimal number of PODs (and their capacity) in an area impacted by a disaster is not an easy thing to do. First, the optimal design of the POD network is related to the facility location problem with service areas, which is a problem notoriously difficult to solve. Second, the nonlinear nature of deprivation costs associated with the lack of access to a life sustaining item complicates things tremendously. A third challenge is that these formulations are intended to be used in the midst of a disaster where time is at the essence, and access to data extremely limited. For that reason, approximate solution approaches could play a key role in providing decision makers with order of magnitude answers about how many PODs are needed and their ideal size.
This paper seeks to help fill this gap with the development of approximate solution approaches for the planning of POD systems. To this effect, the paper introduces an approximate formulation that requires minimum inputs and provides an indication of the optimal number of PODs and their capacities that minimizes total social cost. Social cost is defined as the summation of the logistics costs (i.e., facility, labor and transportation), deprivations cost measured by walking to and waiting at the PODs, and security risk costs resulting from the type of distribution strategy. In order to develop such approximate formulation a series of simplifying assumptions are considered. This document is organized as follows. Chapter 2 reviews current practices in humanitarian logistics modeling. Chapter 3 discusses the model formulation and the simplifying assumptions applicable to PD-HL. Chapter 4 presents numerical results. The paper ends with a conclusions section.

2. BACKGROUND

There is a growing body of literature on the facility location problems that for space reasons cannot be reviewed here. For comprehensive discussions see Daskin (1995), Drezner and Hamacher (2002), and the references therein. In the area of humanitarian logistics modeling a reasonable amount of work has focused on the location of distribution centers and pre-positioned stocks. In Akkihal (2006) an algorithm is developed to locate worldwide aid distribution centers for non-consumable inventories. Balcik and Beamon (2008) and Duran et al. (2008) addressed the problem of locating facilities for humanitarian relief; specifically to determine the number and location of distribution centers and the amount of inventories to be pre-positioned. In (Campbell and Jones, 2009), the main focus is on the pre-positioning of supplies considering failure risk of potential supply points. Ukkusuri and Yushimito (2008) study the location and quantity of inventories with routing considerations. Location and amount of pre-positioned stock considering uncertainties in demand and the reliability of the transportation network is studied in (Rawls and Turnquist, 2010). Following the concepts presented in (Holguín-Veras et al., 2010; Holguín-Veras et al., 2012b; Holguín-Veras et al., 2012c), Yushimito et al. (2012) analyze the spatial location of distribution centers taking social costs into consideration. The model minimizes human suffering through a social cost function defined as a distance-based urgency delivery cost.

A number of authors have studied problems related to the distribution of critical supplies. Haghani and Oh (1996) analyzed the efficient transportation of commodities to the disaster area. Extending this work, Barbarosoglu and Arda (2004) considered uncertainty on the estimation of needs for first-aid goods, vulnerability of suppliers and the availability of distribution routes. Özdamar et al. (2004) model the dynamic transportation problem incorporating updates in the requests for aid and the availability of resources. A hybrid fuzzy clustering-optimization approach based on a three-layer emergency logistics co-distribution framework is proposed by Sheu (2007). For the distribution of critical supplies, Tzeng et al. (2007) proposed a multi-objective (i.e., minimize total logistics cost, minimize total travel time, maximize minimal satisfaction) optimization problem that incorporates pick-up and delivery transfer points.

For the case of location problems with service considerations, Berman and Krass (2002) considered stochastic customer demands and congestion at the facilities. In addition, research has been conducted for the location of urban emergency services spatially distributed queuing systems (Berman and Mandowsky, 1986; Caccetta and Dzator, 2005). Still, though these models include stochastic and congestion considerations, their analyses focused on normal conditions or commercial applications, which greatly differ from humanitarian logistics as has been recognized by a number of researchers (Beamon, 2004; Van Wassenhove, 2006; Holguín-Veras et al., 2010; Holguín-Veras et al., 2012b). The literature review found no publications discussing the optimal location and capacity of PODs. The only planning tool available is the POD calculator from the Unités States Army Corps of Engineers (USACE) (U.S. Army Corps of Engineers, 2010), which contains guidelines for agencies planning for the distribution of emergency supplies. The USACE assumes that victims will drive through a POD and are served without leaving their vehicles and that each vehicle—representing an average family of three—will receive the set of commodities required for a day. The models
also assume that a well-planned and operated POD with one lane of traffic and 3 loading points—servers—
can service 140 cars per hour (i.e., about 5,000 people operating 12 hours per day). In addition, three layout
plans for distribution points are provided, i) Type I: serving 4 lanes (12 servers) of traffic for about 20,000
persons per day requiring a staff of 90 workers/volunteers, ii) Type II: 2 lanes (6 servers) of traffic serving
10,000 persons per day with a staff of 40, and iii) Type III: a single lane (3 servers) that can serve 5,000
persons per day, requiring a staff of 25. This means that, in theory, 100 Type III, 50 Type II or 25 Type I
PODs could serve the needs of 500,000 people. However, the POD calculator does not indicate which
configuration is better. Moreover, the assumptions adopted by USACE, although valid for small emergencies
(e.g., small flooding, blackouts, fires) in developed countries, are not likely to hold in large urban disasters or
catastrophes (e.g., Haiti, Japan), where large proportions of vehicles are destroyed or where the majority of
the population has no access to vehicles.

As shown, the bulk of the literature—with the exception of (U.S. Army Corps of Engineers, 2010)—has
focused on the top layers of the PD-HL process where the main focus is on where to locate facilities to
receive or pre-position commodities, equipment, or personnel. As a result, the study of the local distribution
problem has been limited to flow and transport considerations between these facilities or to demand points.
Moreover, the literature has not studied the design of POD networks or considered the most important
characteristics of humanitarian logistics (Holguín-Veras et al., 2010; Holguín-Veras et al., 2012b),
specifically the implications on human suffering. The importance of an adequate POD network is recognized
by the relief groups that participated in the Sphere Project (The Sphere Project, 2011) that outlines minimum
standards for humanitarian response. (The Sphere Project, 2011) suggests that “…distribution points should
be established where they are…most convenient to the recipients, not based on logistics convenience…”,
“…the number of distribution points should take into account the time it takes recipients to travel to
distribution points…”, “…access to distribution is a common source of anxiety for marginalized and
excluded populations in a disaster situation…” (The Sphere Project, 2011). In terms of food distribution, the
guidelines make a distinction between wet and dry rations. Wet rations refer to the daily distribution of a
cooked meal. These may be provided during the initial days after an emergency or in cases where victims
carrying supplies back to their homes increase their security risks, the displaced population has lost their
cooking utensils or when they are in no condition to cook, among others (The Sphere Project, 2011). On the
other hand, dry rations, are the supplies distributed to be used or cooked by the beneficiaries in their homes
and last for several days (The Sphere Project, 2011). Obviously, the distribution of dry rations requires that
beneficiaries have the minimum conditions (e.g., cooking utensils, energy) to use them. This paper attempts
to fill a void in the literature concerning the planning and design of the POD network, while considering
metrics of human suffering.

3. MODEL FORMULATION

As discussed, one of the objectives of this paper is to develop a planning tool for the optimal configuration of
the POD system that minimizes total social costs. The term “optimal configuration” is used to designate the
duplets of number of PODs and number of servers per POD that minimize the considered costs. The
approach developed uses economic valuation to translate the impacts on waiting and walking into a monetary
metric. There are very important practical reasons to do so. Using a cost measure to distribute and allocate
resources enables to integrate disparate impacts on a compact optimization model thus leading to coherent
results. Following The Sphere Project (2011) and Holguín-Veras et al. (2012b), the model considers a total
social cost function defined as the total of logistics costs, deprivation costs and security risk costs. The
decision variables are then defined as:

\[
\begin{align*}
n &= \text{Number of PODs to serve the impacted area} \\
n &= \text{Number of servers per POD (i.e., lane of aid distribution)} \\
f &= \text{Distribution frequency per month}
\end{align*}
\]
In order to model the planning of the POD network, the following parameters are used and assumed:

- **\( A \)** = Total area impacted
- **\( \Pi \)** = Total population affected
- **\( \varphi \)** = Average family size
- **\( \mu \)** = Service rate per server
- **\( v_w \)** = Average walking speed
- **\( c^h \)** = Fixed facility cost per POD
- **\( c^s \)** = Personnel cost
- **\( c^d \)** = Walking cost per unit of distance
- **\( c^t \)** = Transport cost of a unit of supply per unit of distance
- **\( c^w \)** = Waiting cost per unit of time
- **\( c^r \)** = Replenishment or opportunity cost per unit of supply
- **\( c^i \)** = Inventory and security cost of each unit of supply per day

In addition, to simplify notation, the following auxiliary variables are defined:

- **\( a = A/n \)** = Area covered per POD
- **\( \pi = \Pi/n \)** = Population covered per POD

The simplifying assumptions adopted are discussed next:

- The area impacted is a dense convex polygon in the two-dimensional plane with no geographical barriers, where the population is assumed to be uniformly distributed.
- The area can be partitioned in districts/service areas—of equal size and shape—to be served by a POD. Each district/service area is served by a POD located at the district’s center.
- The probability of failure of a POD is zero.
- The PODs are identical queuing systems with the same capacity, where each POD requires personnel for its operation (e.g., management, crowd control).
- A server—defined as a lane for aid distribution—requires additional personnel for its operation (e.g., unloading, handling).
- The number of individuals that need to be served by a POD in a given day is a function of the affected population in the service area of the POD, a policy for recipient selection policy, and the frequency of distribution strategy.
- Three possible policies for the selection of recipients of supplies at the PODs are considered: (1) \( p^1 \): the recipient is each individual; (2) \( p^2 \): the recipient is a representative of the family who is accompanied by the other members of the family; and (3) \( p^3 \): a recipient is a representative of the family who brings the supplies back to his/her family waiting at home of Internally Displaced People (IDP) camp. The type of recipient to be selected depends on the conditions at the impacted area.
- The service times are deterministic and constant rates.
- There are enough resources to distribute to individuals.
- Logistics costs include a fixed facility cost, a variable labor cost depending on the number of servers and the transportation cost of supplies to the PODs.
- Deprivation costs are captured by the walking and waiting for critical supplies costs.
- Risk cost measures the security risks associated with the ration size distributed. The larger the ration size, the higher the exposure of individuals to be subjected to theft and violence.

The key assumptions and other important considerations are further discussed next.
3.1. Recipient policy implications

As mentioned, depending on the conditions at the impacted area, a distribution policy must be determined in terms of the type of recipient. This policy will have great planning implications as it will determine the number of individuals that will have to walk, wait and be served at a POD. Furthermore, the policy will affect the frequency of distribution strategy. The type of policy and implications are:

- **p1**: the recipient is each individual. With this policy, each individual will have to walk to the POD and wait for service. In a typical day, the number of recipients is an inverse function of the size of the rations handed out. Designating \( t \) as the time duration of the supplies (ration size), the number of times per planning period, \( \tau \), that supplies are distributed to the survivors (frequency), \( f \), becomes \( f = \frac{\tau}{t} \). Thus, in average, the number of recipients in a given day is:

\[
\pi f = \pi \frac{f}{\tau} = \pi \frac{1}{t}
\]  

(1)

- **p2**: the recipient is a representative of the family who is accompanied by the other family members. In this case, each individual has to walk to the POD and wait for service, though only the representative will be at the queue, which will decrease the queue waiting times. The representative then receives the family supplies and is helped by all members to carry the goods back. Since all individuals will receive aid, the number of individuals to be served is:

\[
\pi f = \pi \frac{f}{\tau} = \pi \frac{1}{t}
\]  

(2)

- **p3**: a recipient is a representative of the family who brings the supplies back to his/her family waiting at home or at an Internally Displaced People (IDP) camp. Only the representative will have to walk and wait at the POD. However, as only one individual is receiving the supplies, the ration size will have to be divided by all family members. As a result, it is expected that the frequency of distribution will increase. In essence, fewer individuals, \( \frac{\pi}{\phi} \), will have to visit a POD an increased number of times. The number of recipients is:

\[
\pi f = \pi \frac{1}{\phi} = \pi \frac{f\phi}{\tau}\frac{1}{t}
\]  

(3)

As shown, during the planning period, the aggregated number of individuals visiting the POD is the same as for the other two policies. Assuming \( p^3 \) as a binary parameter that determine the recipient policy used, the number of individuals receiving aid is expressed as:

\[
\pi f = \frac{\pi}{\left((1-p^3)+p^3\phi\right)t} = \frac{\pi}{\left((1-p^3)+p^3\phi\right)t} = \pi \frac{f}{\tau}
\]  

(4)

3.2. Logistic costs

This function takes into consideration the fixed cost of locating a POD, \( c^0 \), plus a variable cost that depends on the manpower required for its operations, \( c^t \). The current formulation disregards the inventory cost as in PD-HL almost all supplies reaching the PODs are immediately used. It is important to mention that as the size of the POD—number of servers—increases so does the personnel required (i.e., the larger the POD the larger the number of personnel needed for management, cargo handling and crowd control). This is not a linear relation. Using (U.S. Army Corps of Engineers, 2010) as reference (U.S. Army Corps of Engineers, 2010), a function was fitted to the values provided for the manpower of the three types of POD layouts. The results indicate that a quadratic function of the form \( \theta k^2 + \beta s + \omega \), where \( \theta, \beta \) and \( \omega \) are parameters, provides a good estimate of the number of volunteers/staff that are needed to operate PODs of different sizes. The
parameters are estimated as $\theta=.074$, $\beta=5.00$ and $\omega=8.33$. It is important to note that, as discussed before, the USACE guidelines may have some limitations. As a result, the number of personnel required to handle a POD after a major disaster is likely to be underestimated, especially for crowd control and security staff.

The logistics costs also consider the cost of transporting the cargo required at a POD from a distribution center (DC). It is assumed that the line haul distance, $d^l$, between a warehouse, randomly located inside the impacted area, and the POD can be approximated by $d^l = \kappa r^A$, where $A$ is the area impacted, and $\kappa \approx 0.52$ is a constant (Larson and Odoni, 1981). On the contrary, if the warehouse is located outside the impacted area, $d^l$ is assumed to be the average distance from the warehouse to the center of gravity of the impacted area $d^{l-c}$ plus the distance between the center to the average POD, $d^l = \kappa c$, with $\kappa \approx 0.383$ (Larson and Odoni, 1981). However, throughout the paper, it is assumed that the DCs are located inside the impacted area.

The amount of cargo required at a POD depends on the type of items supplied to satisfy the needs and the number of people (recipients) to be served. This amount ranges from a bare minimum, i.e., subsistence level, to a higher standard that enables the survivors to satisfy other less urgent needs. The U.S. Army Corps of Engineers (U.S. Army Corps of Engineers, 2010) estimate that each person should receive, as a minimum, a bag of ice (5 kg), a gallon of water (4 kg) and 2 MREs (1 kg) per day. This translates into 5 kg of supplies if ice is not provided, and 10 kg if it is. However, these numbers do not consider that individuals that have lost their possessions have other basic needs (e.g., clothing, kitchen and cleaning utensils, medicine). The minimum standards set by the SPHERE project account for 7.5 to 15 liters (7 - 14 kg) of water consumption per day (without considering water needed for sanitation), and a daily diet consisting on an energy intake of about 2000 KCal that is obtained with a mix of a half kg. of food (e.g., maize, rice, beans, etc.) (The Sphere Project, 2011). The Japanese experience provides some estimates, on average the survivors of the Tohoku earthquake received 20 kg per person-day at the relief center during the first weeks of the disaster (Holguín-Veras et al., 2012a; Holguín-Veras et al., 2012b; Holguín-Veras et al., 2012d). As a result, the amount of cargo handed out at a POD depends on the aid requirements per individual per day $r^l$, the number of individuals $\pi^l$, and the ration size $t$. The amount of cargo is $r^l \pi^l t = r^l \frac{\pi}{t} t = r^l \pi$. To transport this amount to each POD, considering a truck capacity, $\gamma^l$, the number of truck trips required is:

$$\xi = \left[ \frac{r^l \pi}{\gamma^l} \right]$$

(5)

It is important to mention that experiences in recent disasters have shown that small to medium trucks are more suitable for delivering inside urban areas. Additionally, the cycle time of a truck $\delta$, is the summation of the average time to travel the average tour distance at an average speed, $v^l$, the loading times at the warehouse $\tau^l$, and the unloading times at the PODs $\tau^u$. The cycle time could be expressed as:

$$\delta = \frac{2d^l}{v^l} + \tau^l + \tau^u = \frac{2\kappa r^A}{v^l} + \tau^l + \tau^u$$

(6)

Considering that deliveries will be made during the daily hours of operation, $h$, then the number of trucks required will be a function of the total truck trips needed to deliver supplies to all the PODs and the average cycle time. The average total number of trucks $\varsigma$, is:
Assuming a truck cost per hour of $c^2$, and the hourly cost to load and unload the cargo $c^{l-u}$, total transportation cost is:

\[
\text{Transport Cost} = n \xi \left( c^2 \frac{2\kappa c^2 \sqrt{A}}{v^l} + c^{l-u} (t^l + t^u) \right)
\]

Thus, the total logistics cost can be defined as:

\[
H(n, s) = c^n n + c^n n (d^2 + \beta s + \omega) + n \left[ r^f \prod_{i} \frac{1}{n^l} \right] \left( c^2 \frac{2\kappa c^2 \sqrt{A}}{v^l} + c^{l-u} (t^l + t^u) \right)
\]

### 3.3. Deprivation costs

The previous discussion focused on the logistics (or private costs) that are internalized by the relief agencies (i.e., facility, inventory, transportation). However, there are external costs not directly felt by these organizations. In humanitarian logistics, the costs associated with the lack of access to a good (i.e., deprivation costs)—a measure of human suffering—are not internalized (Holguín-Veras et al., 2010; Holguín-Veras et al., 2012b) by the groups doing the distribution. As discussed before, in order to achieve one of the humanitarian logistics primary objectives to minimize human suffering, humanitarian logistics modeling must take into account deprivation costs resulting from distribution actions (Holguín-Veras et al., 2012b; Holguín-Veras et al., 2012c). Although there are many factors that influence deprivation costs, the approach used here is based on two proxies: the travel distance to the POD and the waiting time at the POD.

The walking distance is important because in large urban disasters—where most of the impacted population is in need of aid and access to or use of transportation equipment is limited or nonexistent—individuals may have to walk long distances to the pedestrian PODs. The distance can be Euclidean, network, Manhattan, or any other type of distance measure. Besides the type of distance measured, it is also important to define the distance objective; if for example, the problem is to minimize the average (total) walking distance between the demand points and the facilities, the problem falls under the class of continuous $p$-median problem (Drezner and Hamacher, 2002). The $p$-median facility problem introduced by Hakimi (1964), tries to determine the location of $P$ facilities so as to minimize the average (total) distance between demands and facilities. In contrast, if the objective is to minimize worst performance of the system that is, to minimize the maximum distance from demands to the location of a facility, the problem falls under the class of continuous $p$-center problem. Assuming Euclidean distances and uniformly distributed individuals in the service area, the ideal location of a POD would be at the center of each district (where both the average total walking distance and the maximum walking distance are minimized). In this case, the average travel distance is $d^w = \kappa^c \sqrt{a}$, where $a$ is the area of the district, and $\kappa^c \approx 0.383$ is a constant (Larson and Odoni, 1981). Thus, total walking cost per day is:

\[
\Psi(n, f) = c^d n \pi f \frac{\kappa^c \sqrt{A}}{n} = c^d n \pi f \left( \frac{\kappa^c \sqrt{A}}{n} \right)
\]

To estimate the waiting time, it is assumed that a POD is a queuing system. To define the system, the first step is to identify the arrival process. This is typically done by estimating the inter-arrival time distribution, which requires significant data collection and analysis efforts. Considering the limited amount of time and resources during PD-HL, simplified formulations must be developed. With this in mind, a series of simulations were conducted to estimate the inter-arrival process. The simulations assume that after the
disaster individuals walk at a constant speed $v_w$ towards a POD situated in the center of the district assumed to be a region (square shape) of 1, 4 and 9 square kilometers. Each simulation considered a number of individuals, $\pi^f$, walking to the POD, represented by random uniformly distributed points. Euclidean distances and an average walking speed after disasters $v_w$ of 2.5 km/hr were used to calculate their walking time $t_w$ to reach the POD. For different numbers of individuals and area, 1000 cases were evaluated. In order to test the hypothesis that inter-arrival time could be approximated by an exponential distribution, chi-square tests were conducted. Table 1 shows the simulation results.

<table>
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<tr>
<th>Area</th>
<th>$x$</th>
<th>$\pi/x$</th>
<th>$\pi$</th>
<th>Total distance (km)</th>
<th>Average distance (km)</th>
<th>Average inter-arrival time</th>
<th>Standard deviation inter-arrival time</th>
<th>Failed GOF test for Exponential distribution</th>
<th>% of failures</th>
<th>Arrival rate</th>
<th>Estimated arrival rate</th>
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<td>100</td>
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<td>250</td>
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<td>500</td>
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<td>250</td>
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<td>0.765</td>
<td>0.0022</td>
<td>0.0000</td>
<td>185</td>
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<td>2</td>
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<td>500</td>
<td>383</td>
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<td>0.0000</td>
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<td>909</td>
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<tr>
<td>4</td>
<td>2</td>
<td>500</td>
<td>1000</td>
<td>766</td>
<td>0.766</td>
<td>0.0006</td>
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<td>942</td>
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<tr>
<td>4</td>
<td>2</td>
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<td>5000</td>
<td>3,826</td>
<td>0.765</td>
<td>0.0001</td>
<td>0.0000</td>
<td>1000</td>
<td>100%</td>
<td>8,918</td>
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<tr>
<td>9</td>
<td>3</td>
<td>33</td>
<td>100</td>
<td>115</td>
<td>1.149</td>
<td>0.0080</td>
<td>0.0003</td>
<td>82</td>
<td>8.2%</td>
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<td>250</td>
<td>287</td>
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<td>0.0033</td>
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<td>193</td>
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<td>167</td>
<td>500</td>
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<td>1000</td>
<td>100.0%</td>
<td>5,945</td>
<td>5,950</td>
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</table>

The results indicate that as the population in the service area increases, the average inter-arrival times increasingly depart from the ones estimated by the exponential function. This is consistent with the postulates of the heavy traffic approximation (Kingman, 1962). Consequently, in order to explain the inter-arrival process, regression analyses were performed using the simulation results. For the cases considered, it was found that the arrival rate, $\lambda$, is a function of the walking speed, the number of individuals, and the square root of the area. As it was discussed before, when the $p^r$ recipient selection policy is used only the representative of the family will join the queue, thus the arrival rate of the expected number of recipients joining the queue system is (the constant, $\alpha_v$, depends on the walking speed; for a $v_w = 2.5$ km/hr, $\alpha_v$ is 1.427):

$$
\lambda(n) = \alpha_v \pi^f \frac{\pi}{\sqrt{a}} = \alpha_v \frac{\pi}{\sqrt{\pi}} \frac{1}{\tau} \frac{1}{\sqrt{\frac{A}{n}}} = \alpha_v \frac{\pi}{\sqrt{\pi}} \frac{1}{\tau} \sqrt{\frac{A}{n}}
$$

The next step is to estimate the service rate at a POD. Considering that PODs are designed to distribute life sustaining items, the service at these facilities can be standardized, and could be assumed as constant per server with mean $\mu$. As a reference, the USACE POD service rate is 45 cars per hour per server. Moreover, there are a finite number of individuals seeking supplies at a specific POD, who would be served in a first come first served basis (FCFS).

Another important component for the system is the nature and characteristics of the queue. Assuming constant arrival and service rates with mean $\lambda$ and $\mu$ respectively, and $s$ servers at the POD results in one of
two conditions: i) if \( s\mu \geq \lambda \) then, people are serviced faster (\( s\mu \) is the total service rate at a POD) than they arrive and no queue will form; and, ii) if \( s\mu < \lambda \) then, for the case where \( \pi^f \to \infty \) the queue will increase indefinitely; on the contrary, when \( \pi^f \) is finite, the queue will accumulate but will be cleared over time. It is important to understand that during PD-HL service rates are likely to be smaller than arrival rates, generating congestion at the facilities (case ii), as was the case in Haiti, where individuals had to wait for hours forming vast queues at PODs. With these considerations, a POD is assumed to be queueing system of the type D/D/s/FCFS/\( \infty \)/\( \pi^f \). An approximate formulation of the average waiting time, \( \bar{W}^q \), in queue was then developed, taking into consideration the system’s characteristics. Given constant arrival and service rates, the system could be decomposed to consider each server as a separate sub-system. By construction (considering congestion), the initial \( i = 1 \) individual to arrive at each sub-system can be served immediately without delays, thus the number of individuals that would have to wait is \( \pi^f - s \). Furthermore, the arrival rate for each sub-system would be \( s \cdot \mu \), and the number of individuals to be served by each is \( s \cdot \mu \cdot f \). Now, the time difference between services and the inter-arrival times is \( -\frac{s}{\mu} \), which would be the waiting time, \( W^q_2 \), experienced by the second individual \( (i = 2) \) arriving to each sub-system. From this point on, each additional individual arriving to the queue would have to wait this time plus the waited time of the previous individual. For \( i = 3 \) the waiting time is \( \left[ 1 - \frac{s}{\mu} \right] + W^q_{i-1} = \left[ 1 - \frac{s}{\mu} \right] + \left[ 1 - \frac{s}{\mu} \right] = 2 \left[ 1 - \frac{s}{\mu} \right] \), and for \( i = \pi \),

\[
W^q_\pi = \frac{\pi^f - s}{s}.
\]

As a result, the total waiting time in queue for all individuals in the \( s \) sub-systems can be approximated by,

\[
W^q = s \left[ 1 - \frac{s}{\mu} \right] \sum_{i=1}^{\pi^f-s} \left[ 1 - \frac{s}{\mu} \right] = \frac{1}{2} \pi^f \left[ 1 - \frac{s}{\mu} \right] \left[ \frac{\pi^f - s}{s} + 1 \right] = \frac{1}{2} \pi^f \left[ 1 - \frac{s}{\mu} \right] \left[ \frac{\pi^f - s}{s} - 1 \right]
\]

(12)

And the average waiting time,

\[
\overline{W^q} = \frac{1}{\pi^f} \left[ 1 - \frac{s}{\mu} \right] \left[ \frac{\pi^f - s}{s} - 1 \right]
\]

(13)

The formulation developed for the average waiting time in queue, \( \overline{W^q} \), for this type of queuing system is:

\[
\overline{W^q} = \begin{cases} 
\frac{1}{\pi^f} \left[ 1 - \frac{s}{\mu} \right] \left[ \frac{\pi^f - s}{s} - 1 \right], & \forall \pi^f > s \land \lambda > \mu s \\
0, & \text{Otherwise}
\end{cases}
\]

(14)

Thus, total waiting cost at all PODs in a day is:

\[
\Gamma(n,s,f) = c^n \cdot \pi^f \overline{W^q(n,s,f)}
\]

\[
= c^n \frac{\Pi}{(1-p^2)+p^2 \varphi} \frac{f}{1-\frac{s}{\mu}} \left[ \frac{1}{\alpha} - \frac{s}{\pi^f} \frac{\Pi}{(1-p^2)+p^2 \varphi} \frac{f}{1-\frac{s}{\mu}} \right] \left[ \frac{\Pi}{n(1-p^2)+p^2 \varphi} \right] \frac{f}{\tau} - 1
\]

(15)
3.4. Risk of theft and violence

The distribution of dry rations brings about other risks that must be taken into account when identifying the quasi-optimal POD configuration. One such risk is the one associated with theft or violence. In the words of the Sphere report “...carrying food home would put beneficiaries at risk of theft or violence...[and]...high levels of abuse or taxation excludes vulnerable people...” (The Sphere Project, 2011). These risks may be more or less critical depending on the type of events and the conditions, however they must be considered. This could be done by empirically developing a risk function though there are no data available to do this type of analysis. Instead, and in order to gain insight into the impact of risks on the solutions, it is assumed that the risk of theft and violence (% of cases) is an increasing function of the size of the rations expressed in terms of the distribution frequency, \( f \). The function used is:

\[
    r(f) = \frac{\chi}{f^\phi}
\]

(16)

Where \( \chi \) and \( \phi \) are parameters to be determined empirically. Considering that to maintain a constant supply, when \( p^3 \) is used, the frequency increases by a factor of \( \varphi \), equation (87) can be modified as:

\[
    r(f) = \frac{\chi}{\left((1-p^3)+p^3\varphi\right)f^\phi}
\]

(17)

Thus, the assumed economic valuation to total risk can be expressed as:

\[
    R(f) = c^i\Pi r(f)\left((1-p^3)+p^3\varphi\right)ft = c^i\Pi \frac{\chi}{\left((1-p^3)+p^3\varphi\right)f^\phi} \left((1-p^3)+p^3\varphi\right)f^{\frac{\tau}{\left((1-p^3)+p^3\varphi\right)f^\phi}}
\]

\[
    = c^i\Pi \frac{\chi}{\left((1-p^3)+p^3\varphi\right)f^\phi}^{\tau}
\]

(18)

Where the term \( c^i \) is the corresponding cost of replenishing or opportunity cost of the aid ration lost, \( r(f) \) is the percentage of incidents of theft or violence, and \( \left((1-p^3)+p^3\varphi\right)ft \) indicates the expected aid ration size to be replenished each distribution cycle. Besides the risk of theft and violence resulting from carrying supplies back to their homes or Internally Displaced People (IDP) camps, individuals have to spent resources and efforts securing the supply rations they receive. Assuming a constant consumption rate, the total number of aid units that need to be stored at each distribution cycle can be expressed as:

\[
    i(f) = \frac{1}{2}i(t-1) = \frac{1}{2} \left(\frac{\tau}{\left((1-p^3)+p^3\varphi\right)f}\right) ^{\frac{\tau}{\left((1-p^3)+p^3\varphi\right)f^\phi}} \left(\frac{\tau}{\left((1-p^3)+p^3\varphi\right)f^\phi} - 1\right)
\]

(19)

Assuming a cost, \( c^i \), to inventory/secure each unit of supply every day, total inventory costs are:

\[
    I(f) = c^i i(f)\Pi \left((1-p^3)+p^3\varphi\right)ft = c^i\Pi \tau \frac{1}{2} \left(\frac{\tau}{\left((1-p^3)+p^3\varphi\right)f^\phi} - 1\right)
\]

(20)

Furthermore, “…the frequency of distribution should consider the weight of the food ration and the beneficiaries’ means to carry it home…” (The Sphere Project, 2011). In this sense, the inter agency coordination mechanism of humanitarian assistance that involves key UN and non-UN humanitarian partners (Inter-Agency Standing Committee IASC) provides some additional guidelines: “…ensure that the [food] distribution arrangements (time, place, schedule, size and weight, etc.) do not discriminate against vulnerable or marginalized groups…”; “…arrange food distribution so it does not add burdens on women…”; “…weight of food packages manageable and efficient for women (e.g., 25 kg vs. 50 kg bags, etc.)…” (Inter-Agency Standing Committee, 2006). Consequently, it is important to design a constraint that limits the ration size resulting from the frequency of distribution strategy selected. Assuming a maximum carrying weight, \( C \), the constraint in the ration size is expressed as:

\[
    \frac{\tau}{f^\phi} \leq C
\]

(21)
3.5. Optimal POD configuration

Mathematically, the problem of finding the optimal POD configuration taking into consideration the costs previously mentioned for a period \( \tau \) of operations can be formulated as:

\[
MIN\left( TC_{n,s,f} \right) = c^n n + c^n (\delta s^2 + \beta s + \omega) \tau + n \left( r^{'} \frac{\Pi}{n \gamma^'} \right) \left( c^n \frac{2 \kappa^r \sqrt{A}}{\nu^r} + c^{\ell \cdot u} \left( \epsilon^u + \tau^u \right) \right) + n \left( c^n \frac{\Pi}{f} \left( \kappa^c \sqrt{A} \right) \right) \tau + n \left( \frac{1}{\mu} - \frac{s}{\Pi \frac{\alpha^v}{(1 - p^2) + p^2 \phi}} \right) \left( s + \frac{1}{\tau} \right) + \frac{\Pi}{n(1 - p^2) + p^2 \phi} \left( s + \frac{1}{\tau} \right) + c^n \frac{\Pi}{\tau} \left( \frac{1}{(1 - p^3) + p^3 \phi} \right) \left( f + 1 \right) \tau^r
\]

Subject to:

\[
\frac{\tau}{f} r^{'} \leq C
\]

\[
n \geq 1, \{n \in 1, 2, 3, 4, \ldots\}
\]

\[
s \geq 1, \{s \in 1, 2, 3, 4, \ldots\}
\]

The first term of equation 22 represents the total logistics costs including, the fixed cost of PODs, the manpower cost, and the cost of transporting supplies to the PODs. The second and third terms are the proxies for deprivation cost representing walking and waiting costs, respectively. The last two terms are the risk of theft/violence and inventory/securing costs associated with the distribution strategy. The following section discusses the performance of the model under different assumptions.

4. NUMERICAL EXPERIMENTS

This section discusses the numerical experiments conducted. The first set of experiments assesses the sensitivity of the formulation to changes in the walking, waiting, replenishment and inventory cost parameter values; and the implications of the type of ration distributed (wet vs. dry) on the POD configuration. The second set focuses on the impacts of manpower restrictions. A third set, compares the formulation results with the modeling of different objectives or model constraints. These three sets of experiments assume that \( p^l \) distribution policy is implemented. A final set compares the results obtained when implementing the different recipient distribution policies. For the experiments, it is assumed that a large urban area (square shape) of 100 square kilometers with a population density of 17,000 per square kilometer has been impacted by a major disaster (similar to Port au Prince). It is assumed that the entire population is in need of aid. A cost of 2,000 monetary units per facility per month and a labor cost of 80 monetary units per day are assumed. Frequency is defined in a per month basis (\( \tau = 30 \)). Relief supplies to satisfy the food daily needs, \( r^f \), account to 1 kilogram. As mentioned, during relief operations in large urban areas impacted by a major disaster, small to medium trucks are best suited; consequently, a maximum truck capacity, \( \gamma^r \), of 4 tons is assumed. Given the state of network conditions expected, truck is assumed to travel at an average speed of 5 km/hr. From field observations at both Haiti and Joplin it takes, in average, 0.15 hours for 20 individuals to
load/unload a ton of cargo from a truck. In terms of risk of theft/violence it is assumed that \( \chi \) and \( \phi \) are 10% and 3 respectively. The inventory cost is assumed to be 0.015 monetary units per unit of supply per day.

4.1. Sensitivity of Solutions to Changes in Parameters

This section analyzes the sensitivity of the solutions to changes in the parameter values. The values considered are:

- a) Walking cost: 1, 2.5 and 5 monetary units per kilometer;
- b) Waiting cost: 1, 2.5, and 5 monetary units per hour;
- c) Replenishment cost: 5, 10 and 15 monetary units incident of theft/violence;

As shown in Table 2, there is a tradeoff between the number of PODs, the number of servers, and the frequency of distribution. In cases where the walking cost is greater than the waiting cost, the optimal solution is to open a larger number of PODs (reducing walking distance) with fewer servers. The walking cost may be associated with the type of terrain and the effort imposed on the beneficiaries. It is not hard to imagine the extra effort that is required for the affected population when they have to traverse a mountainous location to reach the POD, instead of a flat terrain. When analyzing the total rations distributed in a day (product of number of PODs, servers and ration size), the solution was found to be very sensitive to changes in the waiting cost parameters and not so much due to walking cost. Moreover, the results confirm the importance of waiting on the total cost as changes in this parameter result in larger costs compared to changes in the walking and risk cost. It is thus important to consider congestion at the facilities to help mitigate the impacts on the affected population. Decreasing the waiting time reduces the exposure of the beneficiaries to other risks and fatigue, and also helps reduce deprivation times. In addition, results (Table 2 a and b) provide an indication of the amount of resources (e.g., manpower) required for the distribution of critical supplies. As shown, a large number of individuals need to be assembled to man the PODs, thus requiring extra logistic efforts. The results in Table 2 also show that the type of ration (i.e., wet, dry) to be distributed has major implications in terms of manpower required. The estimates indicate that the daily distribution of wet rations requires between 15 to 20 times the personnel than distributing dry supplies, resulting from the difference in order of magnitude of the number of PODs required. These numbers reflect the fact that while wet rations need to be distributed daily, dry rations could be optimally distributed in frequencies ranging from 1.5 to 3 times per month (ration sizes lasting between 10-20 days). This illustrates the practical benefits of providing dry rations. However, since distributing dry rations could only be done when recipients have the necessary conditions to use the supplies at home, a number of complementary actions may be required e.g., providing cooking utensils to survivors.

<table>
<thead>
<tr>
<th>Table 2 Results for distributing dry rations</th>
</tr>
</thead>
<tbody>
<tr>
<td>a) Distribution of wet rations.</td>
</tr>
<tr>
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<tr>
<td>------</td>
</tr>
<tr>
<td>1</td>
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<tr>
<td>2.5</td>
</tr>
<tr>
<td>5</td>
</tr>
<tr>
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<tr>
<td>2.5</td>
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<tr>
<td>Total cost (in 1,000s)</td>
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<td>2.5</td>
</tr>
<tr>
<td>5</td>
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</table>


The implications of the distribution of wet rations were illustrated in Haiti. During the initial days after the earthquake relief agencies distributed cooked meals to the population at a limited number of PODs (e.g., the World Food Programme—the largest international organization involved in supplying food-related items—only had 14 PODs throughout Port au Prince during the first weeks of the catastrophe). The insufficient capacity of the POD network created havoc in the distribution process which resulted in human suffering—people waiting for hours in long queues at inclement weather (Cole et al., 2010)—leading to a collapse of social order. The situation slightly improved when their initial effort consisting in daily rations, later shifted—after three weeks—to distributing 25 kgs bags of rice that should last for about 2 weeks (New York Times, 2010). As discussed, any type of distribution effort requires large amounts of manpower. In this sense, recent research (Holguín-Veras et al., 2012a) suggesting the integration of collaborative aid networks (CANs) as part of PD-HL systems is an alternative that can offer the manpower, logistics, and the locations to establish a fast response POD system. These CANs are defined as the collection of individuals and their social connections, logistical systems and physical spaces, which are organized to work sharing the same collaborative objective.

### 4.2. Impacts of Manpower Constraints

The formulation discussed in this section takes into account a constraint in the manpower available. This is important because the experience in PD-HL after large disasters clearly shows that relief agencies tend to have a lot of problems assembling the manpower required to man the PODs. Holguín-Veras et al. (2012a) illustrate the magnitude of the manpower required for the distribution of supplies after Haiti. For example, transporting and handling a semi-trailer with 30 tonnes of supplies from Santo Domingo (Dominican Republic) to Port au Prince required about 22 staff-hours; unloading the cargo to 5 tonnes trucks and transporting the supplies to 5 PODs, about 276 staff-hours; and finally, unloading the supplies at the PODs and splitting and distributing the rations to the beneficiaries about 1320 staff-hours. In essence, while the

<table>
<thead>
<tr>
<th>Number of PODs</th>
<th>Walking cost</th>
<th>Walking cost</th>
<th>Walking cost</th>
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<table>
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<tr>
<th>Waiting cost parameter</th>
<th>Total cost (in 1,000s)</th>
<th>Total personnel</th>
<th>Trucks required</th>
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<tbody>
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<td>Walking cost</td>
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<td>Walking cost</td>
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</tr>
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</table>

<table>
<thead>
<tr>
<th>Waiting cost parameter</th>
<th>Total cost (in 1,000s)</th>
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<th>Trucks required</th>
</tr>
</thead>
<tbody>
<tr>
<td>Walking cost</td>
<td>Walking cost</td>
<td>Walking cost</td>
<td>Walking cost</td>
</tr>
<tr>
<td>1</td>
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</tr>
<tr>
<td>2.5</td>
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</tr>
<tr>
<td>15</td>
<td>$55,593</td>
<td>$59,031</td>
<td>$63,760</td>
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</table>
local distribution required about 12 times the effort of the long-haul trip (290 km), preparing and handling the supplies at the PODs required 60 times this effort. This is coupled with the huge challenge of identifying, organizing, and training these individuals that frequently number in the tens of thousands.

The impacts of limited manpower can be modeled by introducing a constraint, \((h^2 + fs + \omega)n \leq R\), that represents the maximum number of PODs and servers that could be located depending on the manpower, \(R\), available. The base case for distributing dry rations assumes that 4,600 staffers are available, and walking, waiting, replenishment and inventory costs of 2.5, 1, 10 and 0.015 monetary units respectively. The sensitivity analyses consider reductions in the manpower available which are expressed as a percent of the optimal number (i.e., 4,600). As shown in Figure 1, total cost increases non-linearly as personnel available decreases. This reflects the importance of manpower for local distribution. Further analyses of costs show that, although, total cost does not start to ramp up until about 40% of the total manpower, waiting and replenishment costs increased considerably as the available personnel decreased. The walking costs increases at a slower pace as a result of a reduction in the number of PODs to be located which increases the distance to the closest POD. Individual inventory also increases as the ration sizes need to be increased to be able to serve a smaller number of individuals at the reduced POD system. As expected, the cost of manpower decreases linearly with the reduction of available personnel. In terms of transport, this cost is relatively constant for changes in the level of manpower available; in addition, a slight decrease is noticed which is the result of trucks been able to be fully utilized as a higher amount of cargo needs to be delivered to a smaller number of PODs. In essence, when the number of PODs is very low (resulting from limited available personnel), there are large increases in deprivation and risk costs Thus, for the development of response plans and the design of distribution systems, it is important to consider the implications of securing adequate personnel in order to reduce human suffering.

4.3. Impacts of Different Modeling Objectives and Constraints

This section compares the results obtained using the proposed formulation for the distribution of wet rations with results obtained using typical logistics assumptions that only consider logistics costs or capacity constraints. The assumptions considered include: (i) only logistics costs; (ii) maximum average travel distance between demand and supply; (iii) maximum POD capacity; (iv) maximum capacity per server; and, (v)
guidelines from the USACE POD locator model. Results are shown in Table 3. As shown, there are large differences in the results obtained. The proposed POD planning model estimates that a large system with 1006 PODs with 8 servers is required to minimize logistics, deprivation and risk costs. In contrast, a configuration with 1 POD and 1 server minimizes logistics costs but at the expense of a large impact on the suffering of the impacted population. Similar configurations are obtained when constraining the distance between individuals and the PODs. As shown, capacity constraints on the size of the POD system although improving the POD configuration still have a great impact on suffering. Finally, results obtained using USACE’s guidelines also underestimate the number of PODs required thus having large deprivation costs.

<table>
<thead>
<tr>
<th>Model Objective/Constraints</th>
<th>Number of PODs</th>
<th>Servers per POD</th>
<th>People per server</th>
<th>Logistics cost (in 1,000s)</th>
<th>Deprivation cost (in 1,000s)</th>
<th>Total (in 1,000s)</th>
</tr>
</thead>
<tbody>
<tr>
<td>POD Planning (total social cost)*</td>
<td>1,006</td>
<td>8</td>
<td>211</td>
<td>$140,724</td>
<td>$147,843</td>
<td>$288,568</td>
</tr>
<tr>
<td>Only logistics costs</td>
<td>1</td>
<td>1</td>
<td>1,700,000</td>
<td>$10,017</td>
<td>$964,243,082</td>
<td>$964,253,099</td>
</tr>
<tr>
<td>Max. average distance (1 km.)</td>
<td>15</td>
<td>1</td>
<td>113,333</td>
<td>$10,514</td>
<td>$64,456,698</td>
<td>$64,467,212</td>
</tr>
<tr>
<td>Max. average distance (2.5 km.)</td>
<td>3</td>
<td>1</td>
<td>566,667</td>
<td>$10,087</td>
<td>$321,636,115</td>
<td>$321,646,202</td>
</tr>
<tr>
<td>Max. POD capacity (1,000 ppl)</td>
<td>1,700</td>
<td>1</td>
<td>1,000</td>
<td>$68,085</td>
<td>$588,180</td>
<td>$656,265</td>
</tr>
<tr>
<td>Max. POD capacity (2,500 ppl)</td>
<td>680</td>
<td>1</td>
<td>2,500</td>
<td>$33,860</td>
<td>$1,451,010</td>
<td>$1,484,870</td>
</tr>
<tr>
<td>Max. POD capacity (5,000 ppl)</td>
<td>340</td>
<td>1</td>
<td>5,000</td>
<td>$21,603</td>
<td>$2,882,136</td>
<td>$2,903,739</td>
</tr>
<tr>
<td>Max. POD capacity (10,000 ppl)</td>
<td>170</td>
<td>1</td>
<td>10,000</td>
<td>$15,793</td>
<td>$5,735,919</td>
<td>$5,751,711</td>
</tr>
<tr>
<td>Max. POD capacity (25,000 ppl)</td>
<td>85</td>
<td>1</td>
<td>20,000</td>
<td>$12,306</td>
<td>$14,276,492</td>
<td>$14,288,799</td>
</tr>
<tr>
<td>Max. server capacity (1,000 ppl)</td>
<td>170</td>
<td>10</td>
<td>1,000</td>
<td>$37,146</td>
<td>$635,923</td>
<td>$673,069</td>
</tr>
<tr>
<td>Max. server capacity (2,500 ppl)</td>
<td>68</td>
<td>10</td>
<td>2,500</td>
<td>$20,848</td>
<td>$1,526,495</td>
<td>$1,547,343</td>
</tr>
<tr>
<td>Max. server capacity (5,000 ppl)</td>
<td>34</td>
<td>10</td>
<td>5,000</td>
<td>$15,415</td>
<td>$2,988,887</td>
<td>$3,004,302</td>
</tr>
<tr>
<td>Max. server capacity (10,000 ppl)</td>
<td>17</td>
<td>10</td>
<td>100,000</td>
<td>$12,699</td>
<td>$5,886,886</td>
<td>$5,900,584</td>
</tr>
<tr>
<td>USACE Type I - 12 servers</td>
<td>85</td>
<td>12</td>
<td>1,667</td>
<td>$26,269</td>
<td>$1,042,620</td>
<td>$1,068,889</td>
</tr>
<tr>
<td>USACE Type II - 6 servers</td>
<td>170</td>
<td>6</td>
<td>1,667</td>
<td>$27,051</td>
<td>$1,013,699</td>
<td>$1,040,750</td>
</tr>
<tr>
<td>USACE Type III - 3 servers</td>
<td>340</td>
<td>3</td>
<td>1,667</td>
<td>$30,247</td>
<td>$993,249</td>
<td>$1,023,495</td>
</tr>
</tbody>
</table>

* POD Planning tool proposed

4.4. Impacts of Recipient Distribution Policy

As described in Section 3.1, there are different recipient distribution policies put in place by the response organizations. These policies will determine the number of beneficiaries that will reach and enter the queue for service at the POD, thus having great planning implications. The policies considered are: 1) p1: the recipient is each individual; 2) p2: the recipient is a representative of the family who is accompanied by the other family members; and 3) p3: a recipient is a representative of the family who brings the supplies back to his/her family. The POD configuration required when implementing the different policies is shown in Table 4. Results indicate that policies 1 and 2 do not affect the POD configuration, as just smaller PODs are required for the latter. On the other hand, policy 3 requires a fewer number of PODs, thus decreasing the amount of manpower required and total costs. It is important to mention that a larger ration size required needs to suffice the needs of the family group and will require more visits to the POD. The results show that the optimal policy would be to distribute to a representative of a family or group; however, the recipient policy will ultimately depend on the conditions at the impacted area. This section discusses the numerical experiments conducted. The first set of experiments assesses the sensitivity of the formulation to changes in the walking, waiting and risk cost parameter values; and the implications of the type of ration distributed
(wet vs. dry) on the POD configuration. The second set focuses on the impacts of manpower restrictions. A third set, compares the formulation results with the modeling of different objectives or model constraints. For the experiments, it is assumed that a large urban area (square shape) of 100 square kilometers with a population density of 17,000 per square kilometer has been impacted by a major disaster (similar to Port au Prince). It is assumed that the entire population is in need of aid. The experiments analyze the estimated number of PODs, their capacity, and the optimal distribution strategy required for a month of operations.

Table 4: Results from Different Recipient Distribution Policies

<table>
<thead>
<tr>
<th>Policy</th>
<th>Policy 2</th>
<th>Policy 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of PODs</td>
<td>142</td>
<td>142</td>
</tr>
<tr>
<td>Number of servers</td>
<td>4</td>
<td>3</td>
</tr>
<tr>
<td>Ration size</td>
<td>14</td>
<td>12</td>
</tr>
<tr>
<td>(n)(s)(ration-size)</td>
<td>7,952</td>
<td>5,112</td>
</tr>
<tr>
<td>Facilit cost</td>
<td>$284</td>
<td>$284</td>
</tr>
<tr>
<td>Servers cost</td>
<td>$10,060</td>
<td>$8,179</td>
</tr>
<tr>
<td>Waiting cost</td>
<td>$5,885</td>
<td>$6,866</td>
</tr>
<tr>
<td>Risk cost</td>
<td>$8,186</td>
<td>$4,692</td>
</tr>
<tr>
<td>Inventory cost</td>
<td>$5,183</td>
<td>$3,264</td>
</tr>
<tr>
<td>Transport cost</td>
<td>$4,973</td>
<td>$4,208</td>
</tr>
<tr>
<td>Total Cost</td>
<td>$38,206</td>
<td>$31,128</td>
</tr>
<tr>
<td>Total personnel</td>
<td>4,192</td>
<td>3,409</td>
</tr>
<tr>
<td>Trucks required</td>
<td>142</td>
<td>142</td>
</tr>
</tbody>
</table>

5. CONCLUSIONS

This paper proposes an approximate formulation—that requires a minimum number of inputs—as a planning tool to estimate the number of pedestrian Points of Distribution (PODs), their number of servers and the frequency of distribution strategy required in the midst of a disaster. Specifically, the inputs required from the region affected are the area and an estimate of the population in need. The formulation is intended to minimize total social cost, which is defined as the summation of costs of (i) locating the PODs, (ii) manning the servers at the PODs, (iii) transporting supplies to the PODs, (iv) walking to the PODs, (v) waiting times at the POD, and (vi) risk costs associated with the distribution strategy. Walking, waiting and risk costs are introduced to account for the impacts on human suffering.

In addition, the paper discusses a set of numerical experiments. The analyses offered important insights for PD-HL planning. First, the design of an adequate POD system for the distribution of critical supplies must take into account both logistic and social considerations. Logistic aspects help optimize the use of scarce resources while social considerations reduce the negative impacts on human suffering. However, although it may be straightforward to identify the direct logistic implications in terms of costs and resources, quantifying the effects on human suffering (e.g., deprivation costs) may not be so. In this work, walking, waiting and risk costs were used as proxies to account for the impacts on human suffering. It is important to note that multidisciplinary research is still much needed in this area as there are still philosophical, ethical, technical and social dilemmas. In terms of results, the experiments show the importance of considering these proxies for suffering in the performance of the POD network. Although limited, it was found that the POD configuration is a tradeoff between these cost measures. However, waiting costs or congestion at the facilities has the largest social implications.
Second, results highlight the importance of manpower for local distribution. Less personnel available translates in a reduced number of PODs and servers that can be manned which increases total social cost. More importantly, reductions in personnel have a non-linear effect on total costs. Hence, it of great importance to secure the personnel to man the PODs. Third, in addition to the number of PODs and their capacity, the distribution frequency is an important component for determining a quasi-optimal POD configuration. A larger ration size—granted that dry rations can be distributed—decreases the amount of PODs and servers required thus reducing the number of personnel needed to man them.

Fourth, there are important considerations in terms of security, resources available and conditions of the beneficiaries that must be taken into account when selecting the type of goods and the distribution strategy. Depending on the conditions at the disaster area, daily distributions of cooked meals (wet rations) may be required; on the other hand, if possible, rations to be prepared and used at home by the beneficiaries may be most suitable. Results show that depending on which type of distribution strategy the amount of resources required is of order of magnitude larger. As a result, it is imperative that complementary actions be taken to improve beneficiaries’ conditions that will allow for a more efficient distribution of critical supplies. These may entail, for example, to provide cooking utensils, with great planning implications as these items will become part of the critical supplies to be distributed.

As discussed, PD-HL modeling must explicitly consider the impacts on human suffering. In this sense, this formulation is expected to be a useful tool for the planning of POD systems.

6. REFERENCES


