Application of a Humanitarian Relief Logistics Model to an Earthquake Disaster

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Abstract

Humanitarian relief is a key operation after a disaster for people who are isolated in disaster-affected areas and cannot get basic supplies for daily living. Because the demand can be large and unexpected, an efficient humanitarian relief logistics planning becomes extremely important. In a recent paper, Lin et al. (2009) proposed a logistics model for disaster relief operations. In this paper we demonstrate how to apply their model to a case study. The scenario that we have selected is that of an earthquake disaster in Southern California simulated using the HAZUS-MH software. A series of sensitivity analyses is conducted in the paper to provide insights on the influence of various parameter settings to the performance of a disaster relief operation – specifically we study the impact of the depot location, the number of vehicles, and the number of clusters chosen. For the simulated earthquake disaster, our analysis shows that geographic location for the depot is important, increasing the number of vehicles does improve the performance, and that reduction in the number of clusters does not guarantee an improvement in the logistics of humanitarian relief.

INTRODUCTION AND LITERATURE REVIEW

Humanitarian relief operations have drawn significant attention in the past decade because of the huge personal and financial costs associated with natural disasters (e.g. the Indian Ocean tsunami in 2004, the Pakistani earthquake in 2005 and hurricane Katrina in New Orleans in 2005). In the scenario of disasters, a humanitarian relief operation includes transporting supplies into the earthquake-affected areas where people are isolated and where daily supplies are not sufficient without shipments from outside. Because the demand for this scenario is often extremely large and unexpected, how to transport supplies from a major distribution center to clusters (destinations) that are located around the affected area becomes a difficult and large-scale logistics problem. The challenges include how many clusters we want to set up, how many vehicles we want to use, etc. In this paper, an actual earthquake event is studied through a simulation to provide insights on how to organize and execute effective and efficient humanitarian relief logistics planning.

Even though humanitarian relief operations (or often called disaster relief operation) have attracted more research interest in the past few years, as early as 1996, Haghani and Oh (*1*) had proposed a multi-commodity, multi-modal network flow model for disaster relief operations. The formulation of the problem was based on the concept of the time-space network and two heuristic algorithms were introduced. Furthermore, Fiedrich et al. (*2*) proposed a dynamic optimization model to find the best assignment of available resources to affected areas after an earthquake. Barbarosoglu et al. (*3*) developed a mathematical model for assigning helicopters tasks during a disaster relief operation. These two studies aimed at optimal resource assignments during the operation in order to make the operation more efficient.

There are several studies in the literature from the perspective of the supplies or the supply chain inventory control. Horner and Downs (*4*) developed a flexible network flow model in a hurricane disaster relief to provide efficient transport linkages between critical elements of the relief goods' supply chain. Ozbay and Ozguven (*5*) concentrated on development of the general humanitarian supply chain problem by proposing an efficient and quick-response humanitarian inventory management model that is able to determine the safety stock that will prevent disruptions at a minimal cost. Ukkusuri and Yushimito (*6*) considered the prepositioning of supplies for disasters and modeled it as a facility location problem accounting for the routing of vehicles and possible disruptions in the transportation network.

In addition, the major interest of a disaster relief operation in academia is related to the logistics problem during and after the disaster. Ozdamar et al. (*7*) proposed the dynamic, time-dependent emergency logistics planning model for natural disasters. Sheu (*8*) introduced a hybrid method for the emergency logistics problem, which includes fuzzy clustering and multi-objective dynamic programming models. Additionally, a dynamic logistics coordination model for both evacuation and supplies support was formulated in Yi and Ozdamar (*9*). An analogous study was found in Yi and Kumar (*10*) in which the ant colony optimization approach was applied to dispatching commodities to distribution centers and meanwhile evacuate injuries to medical centers. Balcik et al. (*11*) considered a humanitarian relief chain problem and focused on allocating relief supplies and determining delivery schedules for each vehicle. Recently, Lin et al. (*12*) proposed a logistics model to delivery critical supplies in a disaster relief operation. The significant feature of their study was prioritizing supplies and penalizing delivery delays cumulatively to emphasize the different urgent needs for human beings in daily supplies.

Based on the Lin et al. (*12*) model and the solution approach, a real-world earthquake scenario is studied in this paper. An earthquake is simulated by the software HAZUS to estimate the damage and economic losses based on the location and magnitude of the 1994 Northridge California earthquake in the United States. The output of the simulation is converted to useful information required in the logistics model in Lin et al. (*12*). A series of sensitivity analyses are conducted to provide insights on the influence of various resource settings to the efficiency and effectiveness of emergency logistics planning, such as the depot location, the number of vehicles, and the number of clusters chosen. We summarize our contributions in this paper as follows. First, we demonstrate that the risk of a disaster can be simulated through a comprehensive software package provided by the federal agency. Second, we generate useful data required in the mathematical model directly from the simulation output. Third, sensitivity analyses of parameters in the model are conducted to justify their influence on the relief operation performance. Finally, discussions of limitations in this research are provided to provide guidance on how to improve the precision of the analysis by considering more real world scenarios.

HUMANITARIAN RELIEF MODEL AND SOLUTION ALGORITHM

Lin et al. (*12*) proposed a multi-objective, multi-item, multi-vehicle, and multi-period logistics model to optimize delivery schedules of critical supplies in a disaster relief operation. In this paper, we only use their first objective (minimization of total penalty cost) as the objective function to simplify the analysis. The model was developed particularly for delivering relief supplies to disaster-affected areas immediately after a disaster occurs and then lasting for several time periods by a set of vehicles through the existing transportation network. Relief supplies considered in this model contain medicine, water, and food that are identified as the most important and needed supplies for daily living. More importantly, urgency levels of these three supplies are assigned based on the importance for human beings, with medicine as the highest priority, followed by water and then food. The demand of all periods in all locations is assumed known at the beginning of the planning, and it remains unchanged during the planning horizon. The amount of supplies in the distribution center is assumed unlimited. For each assignment of the delivery, a vehicle is assigned a tour to travel and deliver supplies. A tour is defined as beginning at the distribution center, continuing to one or more locations, and then returning to the distribution center.

The model constructed in their paper is an integer programming model, and it is described here for the sake of completeness. The inputs include: (a) T: the set of planning time periods $\{1,2,\ldots,t,\ldots,t_{max}\}$, and t_{max}: total number of planning time periods; (b) J_k: the set of locations which the vehicle will visit on tour k; (c) d_{ijt}: demand of the supply i at cluster j in time t; (d) t_k: travel time required for the tour k; (e) to_i: tolerated delay time of supply i; (f) a_i: unit weight of supply i; (g) b_i: unit volume capacity of supply i; (h) H: total working time available in a single period; (i) W: the maximum loading weight of a vehicle; (j) V: the maximum volume capacity of a vehicle; (k) p_{iu}: the penalty cost of item i at delay level u, and $p_{i\tilde{u}}$: the penalty cost of item i if there is remaining unsatisfied demand after the operation periods. The outputs of this model are: (a) x_{ijklt}: amount of item i delivered to cluster j on tour k by vehicle l in period t for the demand occurred exactly in period t; (b) ω_{ijklmn}: backorder amount of item i delivered at cluster j on tour k by vehicle l in period m to satisfy demand in period n, where $n < m$, and $m, n \in T$; (c) y_{klt}: equal to 1 when tour k is assigned to vehicle l in period t, and 0, otherwise.

Then the formulation of the model is summarized as follows:

$$\text{Minimize} \quad \sum_i \sum_j \sum_{u=1}^{t_{max}-to_i} \sum_{t=1}^{t_{max}-to_i-u+1} \left(d_{ijt} - \sum_k \sum_l \left(x_{ijklt} + \sum_{v=t+1}^{t+u} \omega_{ijklvt}\right)\right) \cdot p_{iu} +$$
$$\sum_i \left(\left(\sum_j \sum_t d_{ijt} - \sum_j \sum_k \sum_l \sum_t \left(x_{ijklt} + \sum_{m>t} \omega_{ijklmt}\right)\right) \cdot p_{i\tilde{u}}\right) \tag{1}$$

Subject to:

$$\sum_k t_k y_{klt} \le H \quad \forall l, \forall t \tag{2}$$

$$x_{ijklt} \le M y_{klt} \quad \forall i, \forall j \in J_k, \forall k, \forall l, \forall t \tag{3}$$

$$\omega_{ijkltn} \le M y_{klt} \quad \forall i, \forall j \in J_k, \forall k, \forall l, \forall t, \forall n < t \tag{4}$$

$$\sum_t \sum_k \sum_l x_{ijklt} + \sum_k \sum_l \sum_{m>t} \sum_t \omega_{ijklmt} \le \sum_t d_{ijt} \quad \forall i, \forall j \tag{5}$$

$$\sum_i \sum_j a_i \left(x_{ijklt} + \sum_{n<t} \omega_{ijkltn}\right) \le W \quad \forall k, \forall l, \forall t \tag{6}$$

$$\sum_i \sum_j b_i \left(x_{ijklt} + \sum_{n<t} \omega_{ijkltn}\right) \le V \quad \forall k, \forall l, \forall t \tag{7}$$

$$x_{ijklt} \ge 0 \quad \forall i, \forall j \in J_k, \forall k, \forall l, \forall t \tag{8}$$

$$\omega_{ijklmn} \ge 0 \quad \forall i, \forall j \in J_k, \forall k, \forall l, \forall m \in T, \forall n \in T \tag{9}$$

$$x_{ijklt} = 0 \quad \forall i, \forall j \notin J_k, \forall k, \forall l, \forall t \tag{10}$$

$$\omega_{ijklmn} = 0 \quad \forall i, \forall j \notin J_k, \forall k, \forall l, \forall m \in T, \forall n \in T \tag{11}$$

$$y_{klt} \in \{0,1\} \quad \forall k, \forall l, \forall t \tag{12}$$

A brief explanation of the formulation is as follows. The objective function (1) is a penalty function that aims to minimize unsatisfied demand during the humanitarian relief operation including the sum of penalty cost incurred in various severe delay levels for different supplies within the operation and the penalty cost accrued if there is remaining demand of different types of supplies that cannot be delivered by the end of the operation. Equation (2) indicates that the total travel time of all tours for any single fleet in the same period cannot be violated available working hours in a single period. Equations (3) and (4) show that delivery units of items only can exist if corresponding tours are selected. Equation (5) shows that the total delivery amount of items cannot exceed the demand during the planning periods. Equations (6) and (7) are loading weight limit and the total volume limit of a fleet, respectively. Equations (8) – (11) are used to ensure that vehicles can only stop and deliver to clusters on tours assigned to them. Finally, equation (12) indicates y_{klt} is a binary variable, indicating that if a tour *k* is selected at time *t* to fleet *l*.

One of the challenges in the model is how to determine tours. One scenario is to enumerate all possible tour combinations of all visiting locations, though this becomes impossible when the size of the problem increases. The authors (*12*) suggested two heuristic approaches to keep the number of tours manageable in order to make the model tractable. One of the approaches, named Vehicle Assignment Heuristic (VAH), is suitable because of its ability of parallel computations. In short, the idea of VAH is that the original problem is divided into several sub-problems with manageable size and thus will make the enumeration of tours possible and practicable. The original problem can be solved by solving these small size problems in parallel. On the average, for the problem sizes examined, the VAH can find the solution within 7% of the optimality in 33 seconds. Due to the requirement of quick response in humanitarian relief logistics operations, we use the VAH as the solution algorithm in this paper.

EARTHQUAKE DISASTER SIMULATION AND DATA COLLECTION

The simulation of the earthquake disaster is executed by the software HAZUS-MH, which is developed by FEMA and is a risk assessment methodology for analyzing potential losses in floods, hurricane winds, or earthquakes. In this paper, the earthquake model in HAZUS-MH MR3 patch 2 version is employed, and it is simulated in the desktop computer with 2.00 GB RAM and with Intel Pentium D 3.40 GHz processor. In addition, the interface and analysis of running HAZUS-MH is on the geographic information system software ArcGIS 9.2 version. More information about the earthquake model in HAZUS-MH can be found at this website (www.fema.gov/plan/prevent/hazus) and in the user manual (*13*).

Earthquake Scenario and Study Region

We selected the Northridge earthquake in California because, in the past 20 years, it was the most catastrophic earthquake in the continental United. The Northridge earthquake occurred on Jan. 17, 1994 at 4:31 AM PST in Reseda, California, which is a neighborhood in the city of Los Angeles, California. The epicenter was at 34°12’47’’N, 118°32’13’’W and it had a recorded depth of 17 km. The earthquake had 6.7 moment magnitude and one of earthquakes with the highest ground accelerations in an urban area in North America.

The study region is the Los Angeles County, California. The geographical size of this region is 4,086.9 square miles and it contains 2,054 census tracts. There are over 3,133,000 households in the region and a total population of 9,519,338 people (2000 Census Bureau data). There are an estimated 2,118,000 buildings (approximately 96.00 % of the buildings are associated with residential housing) in the region with a total building replacement value (excluding contents) of 691,005 million dollars. The replacement value of the transportation and utility lifeline systems is estimated to be 25,498 and 7,421 million dollars, respectively.

Simulation Output

In this section, output from the HAZUS-MH is discussed and summarized. It is particularly noted that the simulation input (e.g., number of households, buildings, etc.) is based on the 2000 Census data instead of the real data in 1994. Therefore, numbers of simulated output (e.g., number of fatalities/injuries) are not identical as the real ones recorded in the earthquake. However, it is expected that simulation software can produce the corresponding valid numbers of damages or losses according to the exact same scenario of the earthquake if it happened on the environment as surveyed in the 2000 Census data.

Four main reports are obtained from the HAZUS-MH: direct damage, induced damage, social impact, and economic loss. First of all, in the direct damage report, the damage condition of buildings, critical facilities (e.g., hospitals, schools, EOCs, etc.), and transportation and utility lifelines (e.g., highway, railways, airport, water facility, etc.) is summarized. About 6.00% of the total number of buildings are estimated to be at least moderately damaged. 91.00% of hospital beds are available for use on the day of the earthquake. In addition, there are 20 bridges with at least moderate damage in this region. Secondly, in the induce damage report, fires following earthquake and debris generation by the earthquake can be found. It shows that there will be 181 ignitions that will burn about 2.29 square miles in the region and that the fires will displace about 15,619 people. Thirdly, data related to social perspectives such as the number of shelters required due to displaced households caused by the earthquake and the number of casualties in four severity levels respectively is presented in the social impact report. This report will be described below in detail since it is directly related to our model implementation. Finally, the economic loss report shows building-related losses were 18,091.68 million dollars, transportation and utility lifeline losses were 25,498 and 9,147.01 million dollars respectively, and other long-term indirect economic impacts (e.g. employment impact or income impact) were that there were total 4,984,395 people who suffered employment impact and the total income impact was 13,242 million dollars.

Three datasets, utility lifeline damage data, number of casualties, and number of displaced households, are most relevant to our study and will be used to extract useful data for the relief logistics model. We summarize these three datasets as follows and explain how these datasets can be employed in the relief operation model.

First, the expected potable water performance data included in the utility lifeline damage data is used to estimate the demand of water after the earthquake. It shows that there are 311,689 out of 3,133,774 households in the Los Angeles County without water service on the first day after the earthquake. 289,636, 246,891, and 55,833 households do not have water service at day 3, day 7, and day 30, respectively. Since the geographic distribution of households without water service is not provided in the simulation output, we assume that the number of households without water in each census tract is proportionate to its demographic number of households. Secondly, number of displaced households is used to estimate the demand of food because those families, suffered damage to their houses, are required to have shelters to live temporarily and are incapable of preparing food by themselves. The estimated number of households displaced is 25,469 according to the simulation and the predicted distribution of them is shown in FIGURE 1. Finally, the number of casualties of severity level 1 is used to estimate the demand of medicine. Four severity levels represent the extent of the injuries, and severity level 1 indicates injuries that require medical attention but hospitalization is not needed. Therefore, medicine is required to be delivered into the disaster-affected areas. The predicted distribution of severity level 1 injuries is illustrated in FIGURE 2, and the total number of injuries in this level is 1,654. It is noted that only casualty data for level 1 in the single family is used because the earthquake occurred at 4 AM and the majority of people were at home during the earthquake.

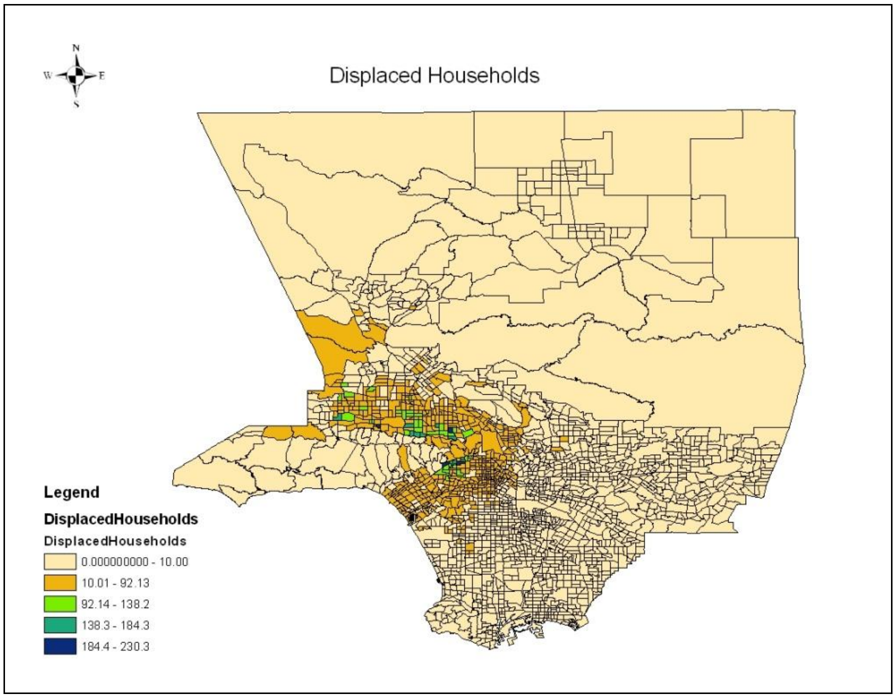

FIGURE 1 Distribution of Displaced Households after Earthquake

Data Collection

In this study, we consider using the depot and clusters to construct the relief supply network, in which supplies are only delivered from a depot to some pre-determined cluster centers instead of delivering to individual receivers or households. The principal reason for doing so is that trucks are typically used to transport supplies from a depot due to the high volume of demands, but it is very difficult for them to drive on local town roads, in particular after an earthquake. Thus, alternative way to deliver supplies is to use trucks to transport between a depot and cluster centers and use smaller vehicles (e.g. pick-up or light truck) to transfer within a cluster area.

Therefore, the study region Los Angeles County must be divided into several clusters. The clustering procedure is performed simply by visualization based on the predicted distribution of demand requests. The default number of clusters is five in this paper, and the clustering result is shown in FIGURE 3. In each cluster, a cluster center is identified to receive supplies from the depot. The criteria for selecting them are: 1) if an emergency operation centers (EOC) existed within a cluster (i.e., there are 12 EOCs in the Los Angeles county, and all of them remain completely functioning based on the simulation), the highest priority will be given to them to be selected, and 2) if an EOC cannot be found, a city or town is selected that is closest to high demand areas. As a result, five cities are selected as cluster centers: Calabasas, Santa Clarita, San Fernando, Pasadena, and Culver City, where the last three cities are EOCs.

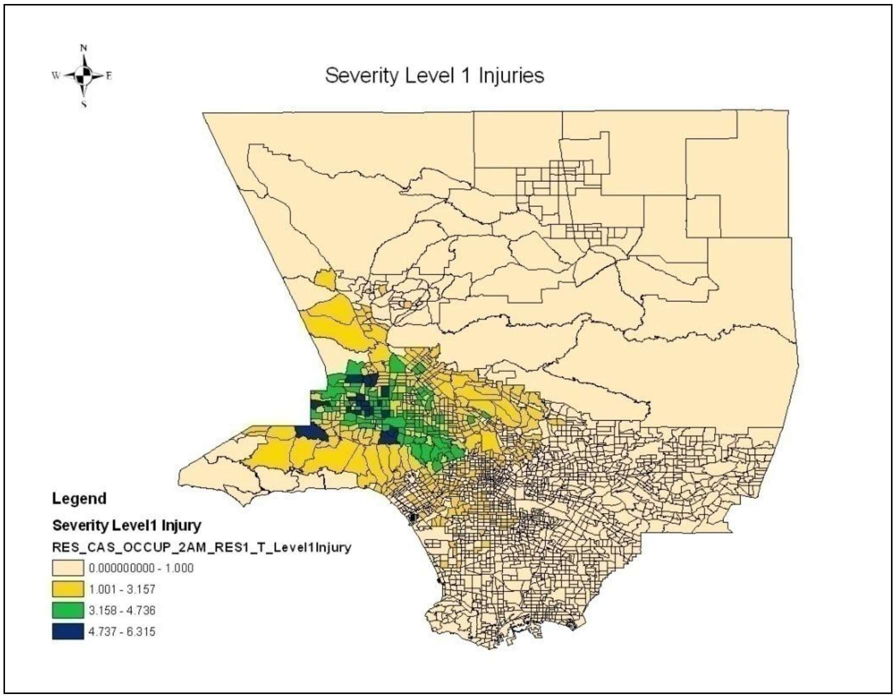

FIGURE 2 Distribution of Severity Level 1 Injuries after Earthquake

Demand distributions from FIGURES 1 and 2 are aggregated directly from all census tracts within each cluster. However, water demand in each cluster is calculated based on the total number of demographic households in it and is obtained by dividing proportionately the total number of households without water service at day 1. After the data aggregation process, however, only "one-time" demand is available. In our application, consecutive data for some time periods is more desirable for us. Therefore, data estimation is required to obtain multiple periods demand data.

As described above, the number of households without water service is represented with different time periods, and it can be interpreted as the recovery speed from the earthquake. We made an assumption that all supplies will have the same recovery speed as the water service supply. The data of water service is used and an exponential fitting function is found to fit this data. The function is $y_i = D(t_1) \cdot (0.961985^{t_i})$, where $D(t_1)$ is the demand obtained from the data aggregation process directly, and t_i is the time period. Therefore, multiple periods of demand data for three supplies can be estimated according to this function.

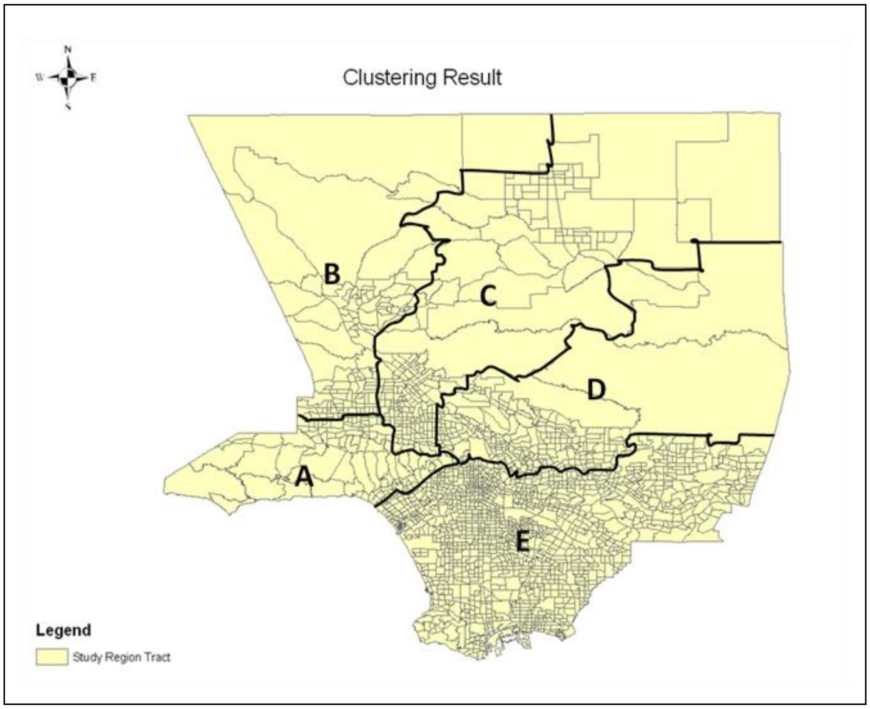

FIGURE 3 Clustering Result in Los Angeles County

RELIEF MODEL IMPLEMENTATION AND SENSITIVITY ANALYSES

In this section, we will discuss how to implement the relief logistics model, and conduct sensitivity analyses to obtain insights on humanitarian relief logistics in a disaster scenario. Some parameters determined in Lin et al. (*12*) are applied in this paper as well. However, there are some of them are different from the previous paper. Instead of using the number of vehicles as the unit of the transportation mode, we use a "fleet" as the unit representing a group of vehicles (e.g. 10-20 vehicles) and in which each fleet has the exact same tasks during the operation. In addition, while the travel time between the depot and clusters or between clusters was obtained by a random generator in their work, in this study, however, the real travel time between any two cities is calculated from a map and the condition of the transportation network system (e.g. highway, local roads) is used to determine the route between any two locations.

Travel Time Estimation

The travel time estimations are required in the model for trips between the depot and any of the cluster centers and between any two cluster centers. The shortest travel time between any locations can be estimated easily by any on-line maps providers (e.g. Google Maps, MapQuest, etc.). In our study, we use Google Maps to choose the shortest travel distance route and the travel time can be readily obtained. However, the shortest travel time routes determined by map must be modified to reflect the roadway and infrastructure damage caused by the earthquake.

According to the U.S. Department of Transportation's report (*14*), some serious damage occurred in the major highway systems inside the Los Angeles county, including I-5 at Gavin Canyon segment, I-5 and SR-14 interchange, I-10 at La Cienega Blvd., Venice St., Washington St., and Fairfax St., SR-118 Mission/Gothic segment. If the route determined by map providers has passed through these sections, a detour is required to proceed to avoid the interrupted roads. Detour suggestions were also provided in (*14*), and, based on these detour suggestions, we modify the routes between any two locations if required. Once the tour is modified, estimated travel time of the tour can be updated. The travel time has two estimates: the normal travel time and the travel time in traffic. The average of these two estimates is used because congestion is expected in some segments on the transportation network system.

Implementation Results and Relief Performance

We first show the implementation results in this study. San Fernando is selected as the depot and all shipments delivered to cluster centers will come from this location. The planning length is 7 days and the demand for different types of supplies is obtained based on the exponential fitting function described above. Furthermore, we assume there are 10 fleets of vehicle teams joining this operation (20 vehicles in each fleet). For each type of item, the allowable delay periods are given as one day for medicine supplies, two days for water supplies, and three days for food, respectively. The penalty cost is also given with an exponential increasing trend (i.e., one more period of delay will cause exponential increment in penalty cost instead of linear one).

The result reveals that a total of 308 shipments are delivered by 20 fleets of vehicles in 7 days, and that is equivalent of 6,240 times of vehicle shipments. The medicine supply is 100% satisfaction of demand in all five clusters, while the water supply and food supply are 47.66% and 33.72% satisfaction of demand. It is interesting to show that only 23.54% to 33.92% of supplies are delivered immediately when the demand requests are made. It is clear that the allowable delay becomes an advantage to take for the decision makers if the demand is large and uneasy to satisfy completely.

Sensitivity Analyses

The main purposes of this paper are not only to implement a mathematical model in a real world disaster scenario as described in above section, but also to provide sensitivity analyses for some parameters that were simply defined by authors directly in a previous paper (*12*).

Analysis One: Location of the Depot

The first analysis of interest in this study is the impact of the location of a depot. Three locations, including San Fernando, Pasadena, and Culver City, among 12 EOCs existing in Los Angeles County are chosen as the depot candidates because their locations are closer to the earthquake-affected areas. We consider choosing EOCs as the depot candidates because their functionalities are designed to prepare and respond in disaster relief operations.

First, we consider the average travel distance and average travel time between three depot candidates and cluster centers, respectively. The shortest average travel distance is obtained when San Fernando is selected as the depot (22.3 miles), followed by Culver City (27.7 miles), and then Pasadena (28.8 miles). The average shortest travel time is also obtained if San Fernando is selected (40.5 minutes), while it takes longest time to travel when Culver City is selected (64.8 minutes) as the depot though it ranks second on the average travel distance. The reason is because it is required to use I-405, which is the one of highest traffic flow highways in Los Angeles metro areas, for Culver City to be connected to two cluster centers.

By implementing the relief logistics model and using three different locations as the depot, the penalty cost due to unsatisfied demands is obtained by the VAH algorithm described in section 2, respectively. We use 10 fleets of vehicle as the available transportation mode to test the performance of this analysis. The solutions from the VAH show that the penalty cost incurred (based on the penalty cost settings for various severities of delay) for San Fernando, Pasadena, and Culver City are 9,684,836, 12,853,754, and 10,122,208 units, separately. It is evident that San Fernando is the best candidate to be chosen as the depot in this earthquake scenario.

Analysis Two: Number of Fleets Used in Delivery

The second analysis discussed in this paper is the impact of the number of fleets employed in the relief operation. It is common sense to assume that relief operation performance improves when more fleets are employed. However, a decreasing marginal return in value is to be expected as additional fleets are employed and the cost of adding each additional fleet will ultimately determine the best number to use.

We consider that the number of fleets used is from 10 to 20. It is probably not a good idea to use too many different fleets in an operation since it will increase the difficulty of co-ordination among these fleets. The operation performance for various numbers of fleets employed in the operation is shown in FIGURE 4. From the figure, the penalty cost is decreasing approximately linearly while the number of fleets is increasing. Based on our calculation, the reduction of the penalty cost is about 0.47 millions units when one more fleet is added to join the relief operation. Therefore, the trade-off of the penalty cost and the number of fleets used for the decision maker is relying on the cost of hiring a fleet. In our case, if the cost to add an additional fleet in the relief operation is less 0.47 millions units, it is worth employing an additional fleet in order to reduce the penalty cost due to unsatisfied demand. However, not only is cost not necessarily linear increasing when more fleets are employed, but it is not the only factor affecting the relief operation decision. We will provide more discussion in the next section to address this issue.

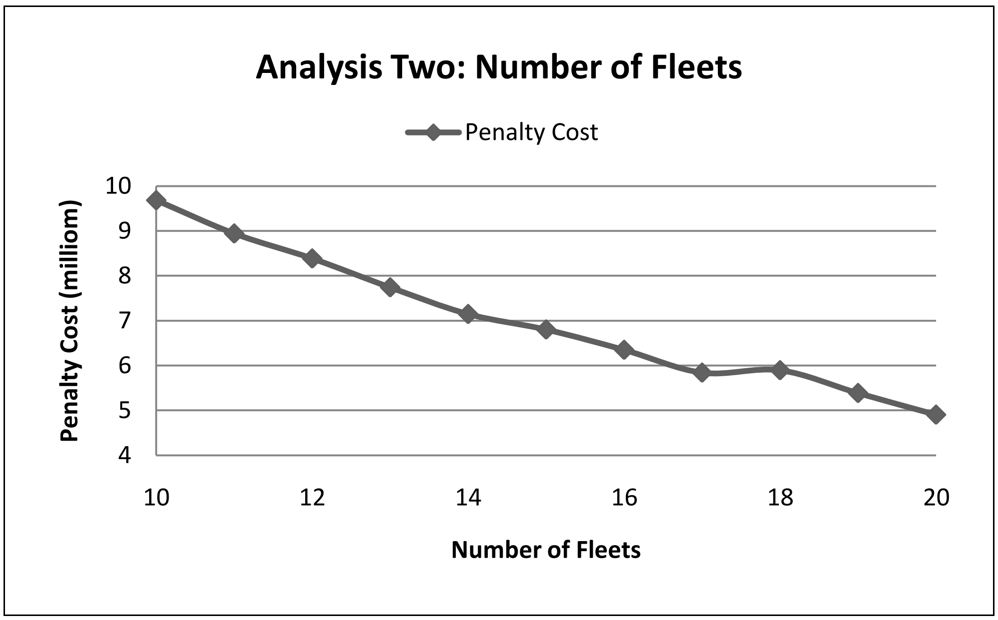

FIGURE 4 Performace of Relief Opeation with Various Number of Fleets

Analysis Three: Number of Clusters

The next interesting question we want to analyze is whether the number of clusters determined will also affect relief operation performance. We analyze this question by reducing the number of clusters in our case from the default of 5 clusters to 4 clusters, and then 3 clusters. The principle of reducing the number of clusters is limited to combining the current five clusters to obtain the desired number of clusters (as opposed to considering a re-clustering process). In addition, we also only allow clusters that can be combined if they are adjacent to each other. For example, clusters A and B can be combined together, and clusters A, B, and C can be combined as well, but clusters A and D cannot be combined together.

For the 4 cluster case, we observe that cluster B and cluster D are two clusters with lower demand requests, so it is reasonable to combine these two clusters to others. So, there are four situations: 1) cluster B combines with A, 2) cluster B combines with C, 3) cluster D combines with C, and 4) cluster D combines with E. Based on the same method, we can reduce one more cluster so that only three clusters remain in the operation. Therefore, for the 3 clusters case, four situations are considered: 1) combining clusters A, B, and C, 2) combining clusters B, C, and D, 3) combining clusters A, D, and E, and 4) combining clusters C, D, and E. It is noted that when three clusters are combined together, the cluster center in the middle of three is used as the new cluster center, while when two clusters are combined, the cluster center of the cluster with higher demand is used as the new cluster center.

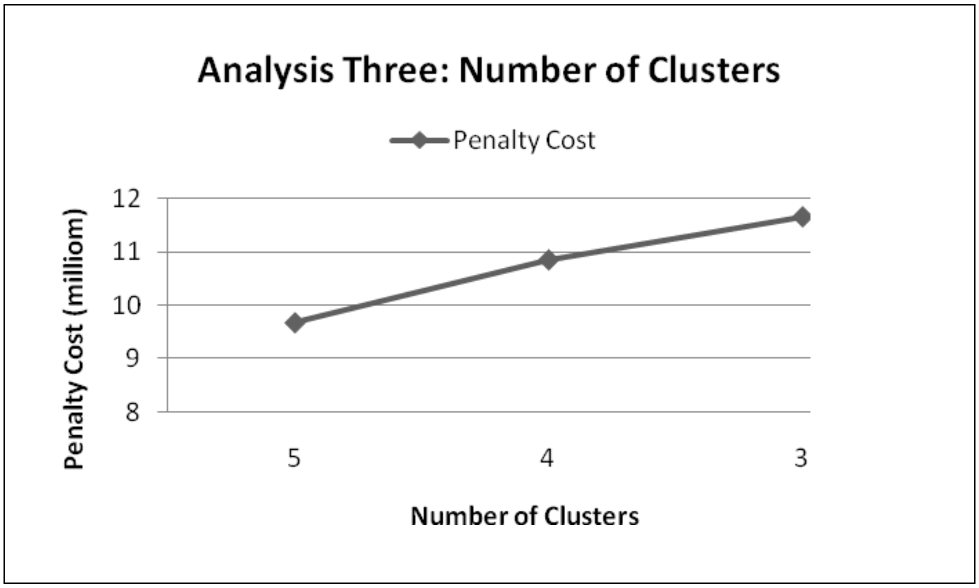

FIGURE 5 Performace of Relief Opreation with Various Number of Clusters

The relief operation performance for different numbers of clusters is shown in FIGURE 5, where the penalty cost for 4 and 3 clusters is represented by the average performance of the four situations as described above, respectively. It shows that the penalty cost increases gradually when the number of clusters decreases from the default 5 clusters. A detailed numbers (before calculating the average performance) reveals that only when clusters A, B, and C are combined as a cluster, and thus only three clusters are formed (i.e. situation 1 in the 3 clusters case described above) in the operation, the performance is slightly better than that using five clusters. However, other combinations of clusters combining together to reduce the number of clusters (either 3 clusters or 4 clusters) can only give worse performance than the 5 clusters case. From the result of this analysis, we also suggest that the number of clusters is not the only factor should be considered in processing the clustering procedure; in fact, the back-end delivery (i.e., from cluster centers to individual families or people) and the cost of operating a cluster center are also important for relief logistics decision makers to consider.

DISCUSSION

In this research, we concentrate on implementing the humanitarian relief logistics model in a real earthquake scenario, and using the disaster risk assessment software to simulate the earthquake and to extract data from the simulation outputs. In addition, some sensitivity analyses are conducted to provide insights into how different parameter settings will impact the humanitarian relief operation performance. However, some limitations are recognized in this paper.

First of all, the transportation network conditions are not fully considered in this research. In our analysis, only the damage of highway systems was considered and detours were employed when the regular route has passed through those damaged segments. However, the transportation network condition is more complicated than that especially after a disaster. For example, congestion is the situation we will expect on major highway systems around the earthquake-affected areas. The challenging issue regarding congestion is that the traffic flow after a disaster is not as predictable as the daily congestion situations. Therefore, it also increases the difficulty of controlling the impact of congestion on the transportation network. In other words, travel time estimation, an important input to the model, can not reflect the real required travel time as well.

Furthermore, relief operation decisions are affected by multiple factors that are not considered in this paper. In sensitivity analyses, we use penalty cost as a measure to evaluate situations with different parameter settings. However, relief operation decisions do not solely depend on a single factor. For the depot locations explored in the first sensitivity analysis, the penalty cost is the only measure to determine which depot candidate is better than others. As a matter of fact, more factors (e.g., connection with other cities outside the disaster-affected area, convenience of loading and unloading supplies) will be involved as considerations when locating a depot.

The impact of the number of vehicle fleets and the number of clusters needs more detailed evaluation. For example, if we add an additional fleet, the cost for doing so may not be linear and may reflect economics of scale. Regarding the choice of the number of clusters there are other issues that are of significance. For example, the number of clusters is typically considered sufficient if an acceptable number of demand points (e.g. 90%) are contained in clusters. Therefore, it may not be possible to reduce the number of clusters below a certain level. A final point is regarding delivery of items from a cluster center to demand points in a cluster. Our model does not focus on this local delivery of items. If the size of a cluster is large (which happens when the number of clusters is small) this local delivery can be costly and consume significant logistic resources. All of these factors are recommended for future model enhancement.

SUMMARY AND CONCLUSIONS

In this paper, we show how a humanitarian relief operation model can be used in a disaster relief scenario through the application of the disaster risk assessment software HAZUS-MH. We simulated the earthquake in Northridge, CA in 1994 and identified the most important outputs related to the input of the relief operation model. Methods of data aggregation and data estimation were introduced based on the information given by the software outputs. Some sensitivity analyses were conducted in this research in order to justify the influence of these parameters on the performance of the relief logistics operation.

We first found the best location in this area that can be used as the depot to receive and distribute supplies from other states or countries. The analysis showed that a good geographic location is very important for a depot. Having good connections with other cities plays an important role in determining the depot location. Besides, we found that performance can be improved if more fleets are employed in the operation but it is subject to the cost of adding an additional fleet. Finally, reducing the number of clusters is not necessarily the best way to improve the relief logistics' performance. In fact, keeping a sufficient number of clusters might not decrease the logistics performance based on the analysis.

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