

Preparing for Disasters: Medical Supply Location and Distribution

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We propose a stochastic optimization approach for the location and distribution problem of medical supplies to be used in disaster situations. We develop a robust decision support mechanism, which is serviceable under the wide variety of possible disaster types and magnitudes. In preparation for disasters, we develop a stochastic programming model to select the storage locations of medical supplies and required inventory levels for each type of medical supply. Our model captures the disaster specific information and possible effects of disasters through the use of disaster scenarios. Thus, we balance the preparedness and risk despite the uncertainties of disaster events. Moreover, we propose mixed integer programming models for loading and routing of vehicles to transport medical supplies for disaster response, which requires the evaluation of up-to-date disaster field information, as well as disaster preparedness. We present a case study of our models based on two earthquake scenarios in the Seattle area.

Key words: stochastic programming, disaster management, emergency management, disaster preparedness, disaster response, medical supply location and allocation

1. Introduction

Decisions to support preparedness and response activities for disaster management are challenging due to the uncertainties of events, the need to balance preparedness and risk, and complications due to partial information and data. We introduce mathematical programming models to plan the storage and distribution of medical supplies to be used in emergencies in the Seattle region, which is vulnerable to earthquakes. We determine the storage location and inventory levels for medical supplies before an event occurs, to balance the risk of incurring earthquake damage themselves yet providing fast distribution to hazardous areas. After the onset of the disaster, we optimize the delivery of medical supplies to hospitals to reduce travel time, using up-to-date information on where the needs are greatest and recognizing that roads may have sustained damage. Our methodology finds a robust solution to the medical supply distribution problem at a city level covering the unique characteristics and effects of possible disaster scenarios as well as incorporating general disaster management principles. This research is developed in the optimization platform called Geospatial Optimization of Strategic Information Resources, which is a part of the Pacific Rim Visualization and Analytics Center (PARVAC) at the University of Washington. The output from the optimization model is incorporated into a simulation with visualization (Campbell et al. 2008).

In the Seattle area, hospitals use their own or shared warehouses to hold inventories of medical supplies that are sufficient for their daily operations for a certain period of time (e.g. 30 days). Our goal is to select an appropriate subset of the same warehouses to store additional medical supplies for post-disaster use by balancing the risks associated with timely delivery of medical supplies across earthquake scenarios. For example, our model may recommend that specific warehouses store 32 days of medical supplies instead of 30 days to be better prepared for a disaster. We also use our models to create transportation plans, including number of vehicles and routes, to deliver the medical supplies from their storage locations to the hospitals where they are needed.

We present decision-making models for the disaster planning and responding team for both preparedness and response phases of the disaster management process focused on distribution of

medical supplies. Figure 1 summarizes the optimization models developed and the information flow between the planning and responding teams and the models. For the preparedness phase, we develop a two-stage stochastic programming (SP) model, which selects the best storage locations from possible warehouses and determines their inventory levels. The SP model can incorporate the priorities of hospitals for particular medical supplies as well as specific disaster scenarios with transportation and demand estimates. Our SP model returns the recommended warehouses with inventory levels for preparedness teams. Our SP model also determines the amount of medical supplies to be delivered to hospitals for each scenario during the second stage. This aggregated decision is fed into a mixed-integer programming (MIP) model to convert the solution of the SP model to vehicle assignments and routing for each scenario. As we discuss later, this information can be used to prepare the number of vehicles to be available at each warehouse, as well as a few preplanned routes, so the vehicle drivers have an initial emergency transportation plan.

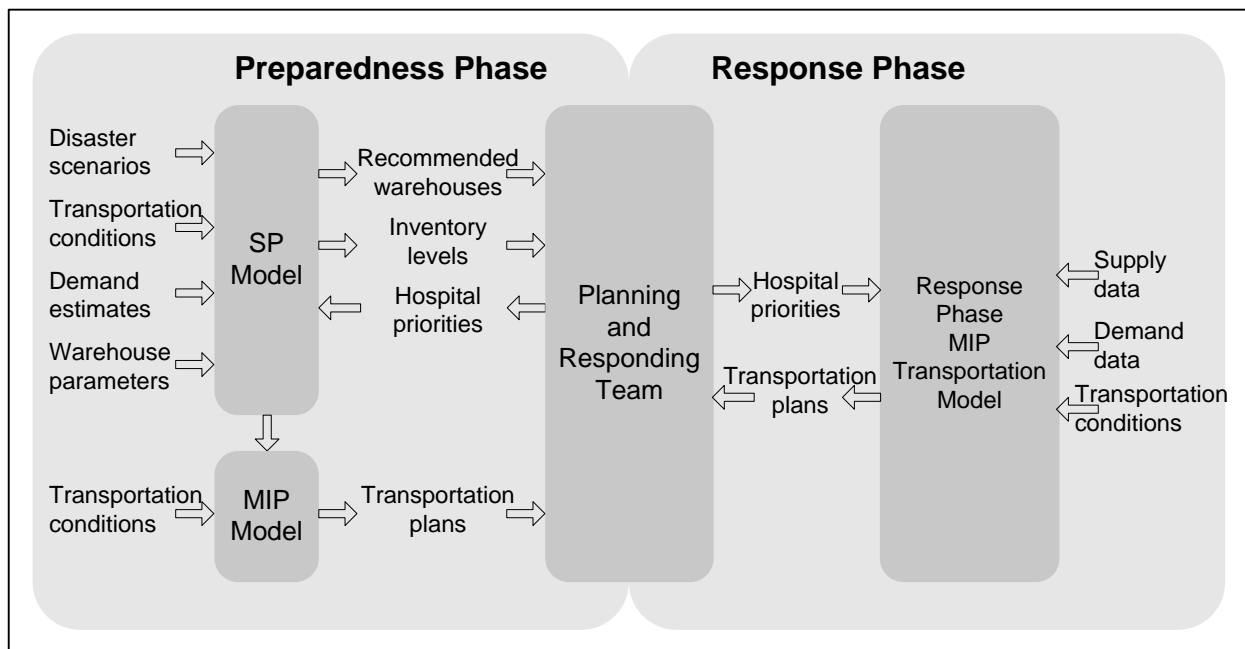


Figure 1 Information flow between optimization models and command center in disaster management

In Figure 1, the MIP transportation model can also be used in the response phase. During the response after an earthquake, the same transportation model can be used with updated information on road conditions, the current amount of medical supplies available, and the current need for medical supplies to provide a revised transportation plan with detailed routes. Because similar problems have been solved to obtain the initial transportation plan, the response phase MIP transportation model can be solved relatively quickly.

Stochastic programming is an appropriate tool for planning in the preparedness phase due to its ability to handle uncertainty by probabilistic scenarios representing disasters and their outcomes. SP has been successful in many applications related to disaster management (Cormican et al. 1998), (Pan et al. 2003), (Barbarosoglu and Arda 2004), (Beraldi et al. 2004), (Lamiri et al. 2006), (Chang et al. 2007), (Morton et al. 2007).

In the preparedness phase, the problem is similar to a facility location problem, which has a two-stage nature: choosing the locations before the demand occurs and reacting once the uncertainty has been resolved. For this problem, using a scenario approach has the advantages of having

more tractable methods allowing parameters to be statistically dependent, which is a realistic characteristic (Snyder 2006). Different than the applications in the current Operations Research and disaster/emergency management literature, we propose a methodology to solve the location and allocation problem of emergency supplies by defining two stages, one corresponds to the preparedness phase and the other corresponds to the response phase. Although Barbarosoglu and Arda (2004) utilize a two-stage SP model for transportation planning in earthquake response, they seek optimal transportation plans and define both stages in the response phase. Their first stage covers the early response phase depending on the earthquake scenarios, and their second stage covers response by the impact scenarios that are detailed branches of the earthquake scenarios.

For a different problem than ours, Beraldi et al. (2004) use a stochastic integer formulation under probabilistic constraints. They solve for the location and assignment of emergency vehicles and utilize probabilistic constraints to ensure the demand of service requests are satisfied at a prescribed probability level. We penalize unsatisfied demand, recognizing it is impossible to satisfy demand under all scenarios. However we add a constraint to limit the total penalties incurred from unsatisfied demand. We use the penalty coefficients to capture time delays and increased costs in obtaining medical supplies that must be obtained from facilities outside of the Seattle area.

The problem of locating and distributing rescue resources for flood emergency is studied by Chang et al. (2007) for optimizing the expected performance of the rescue operations under possible flood scenarios. In contrast to our predetermined demand points, namely hospitals, their demand locations are uncertain and depend on the level of flood in each scenario. Another difference is that their scenarios describe only the demand locations and amounts, while our scenarios include demand amounts (at fixed locations) and parameters that affect transportation times.

Although we focus on managing the impact of uncertainty in disaster preparedness and response, the disaster management literature includes several approaches, other than SP, for location of emergency supplies facilities. Depending on the unique characteristics of the large-scale emergency problems, they are classified as either a set covering, P -median, or a P -center problem (Jia et al. 2007). Brotcorne et al. (2003) classifies the location and assignment of ambulances and other emergency vehicles into three model types: deterministic models, probabilistic queueing models, and dynamic models. Although both problems have similarities (i.e. uncertain demand), our emergency supply transportation problem allows several demand locations at a time whereas the ambulance routing focuses on individual demand points. We assume a constant number of vehicles at each medical supply storage location, whereas determining the minimum number of ambulances and their locations is another aspect studied by Alsalloum and Rand (2006) and Rajagopalan et al. (2008). The former uses goal programming for locating vehicles with maximum expected demand as well as the satisfaction of demand, whereas the latter offers a model to achieve dynamic redeployment of ambulances due to the fluctuating demand in time. A vehicle routing problem formulation for logistics planning in emergency situations that involve dispatching commodities (i.e. medical supply and personnel) to distribution centers in affected areas is provided by Ozdamar et al. (2004). Rather than probabilistic demand, they use demand forecasts of future periods in their multi-period setting. Evacuation operations have also unique settings and assumptions. A location and routing network-flow model with personnel allocation that maximizes the coverage area for support and evacuation operations is presented by Yi and Ozdamar (2007). Another location problem with capacity decisions is given for emergency cleanup equipment in response to an oil spill (Iakovou et al. 1996).

In scenario based modeling of disaster management process, the selection of scenarios and their parameters are of critical importance and requires the contribution of technical disaster experts. In this approach, the identification of scenarios and assigning probabilities are difficult tasks and the general intention is to identify a relatively small number of scenarios for computational reasons, however this limits the range of future states (Snyder 2006). Although there are applications that

present optimal ways of selecting disaster scenarios in the literature (Jenkins 2000), we determine our earthquake scenarios based on expert information; specifically the Department of Earth and Space Sciences at the University of Washington. The Cascadia Fault (Cascadia Subduction Zone) (CREW 2005) and Seattle Fault (Stewart 2005) earthquakes are the two main disasters threatening the Seattle area. In order to capture the variations in the effect of disaster events due to business vs residential hours, we extend the number of our scenarios to model working hours, rush hours and non-working hours for both earthquakes. The probabilities of scenarios for working hours, rush hours, and non-working hours are weighted by the number of hours for each category (48 for working, 30 for rush hour, and 90 for non-working out of 168 hours in a week), as described later in Section 5.

The rest of the article is organized as follows. In Section 2, we present a two-stage SP model for warehouse selection and allocation of medical supplies for disaster preparedness. We provide a mixed-integer programming (MIP) model to convert the solution of the SP model to vehicle assignments and routing in Section 3. Then, Section 4 provides an MIP model for the vehicle routing problem of medical supplies in the response phase. The MIP model in Section 4 is similar to that in Section 3 but allows for updated information on road conditions and demand that were not predicted in the SP scenarios. In Section 5, we present a case study of preparing for potential earthquakes in the Seattle area. Finally, we provide our conclusions and observations on modeling the problem and case study in Section 6.

2. Stochastic Programming Approach for Disaster Preparedness

Stochastic programming is an effective tool for incorporating uncertainty into modeling of optimization problems, which makes it a natural choice for disaster management where events of varying types and magnitudes are difficult to predict. A two-stage SP model is proposed for the medical supply location and allocation problem at a city level. The first stage incorporates the selection of the warehouse locations for medical supplies and the inventory levels for every type of medical supply in the favorable warehouses. After the onset of the disaster, the SP approach allows a set of recourse decisions made in the second stage that can provide a delivery plan of medical supplies from warehouses to hospitals accepting the first stage selection of warehouses and their inventory levels. We use event scenarios to incorporate the probabilistic aspects of disasters. The optimal policy from our SP model is a single pre-event policy of warehouse selections and inventory levels and a collection of recourse decisions defining which second-stage action, namely transportation plans, should be taken in response to each disaster scenario.

The transportation plans provided by the SP model are aggregated plans. To convert them to a detailed transportation, we developed a vehicle assignment MIP model. It solves for the optimal routing of vehicles as well as their load amounts for each scenario that is consistent with the aggregated plan. This MIP model is discussed in Section 3, and a variation of the model is used in the response phase optimization model presented in Section 4.

For each earthquake scenario, the instantaneous rise in the number of patients in hospitals and the vulnerability of the transportation infrastructure are specified to determine the demand for medical supplies at hospitals and the transportation durations in the city. In our case study presented in Section 5, we use studies on the earthquakes in the Seattle area with populations densities and geographical information to estimate the medical supply demand amounts at hospitals and transportation durations from warehouses to hospitals, with occurrence probabilities. We now present our two-stage SP.

Stage 1 - Warehouse selection and inventory decisions

The index sets employed in the formulation of the first stage are the sets of warehouses (I), and the types of medical supplies (K). In the first stage of the SP, the binary decision variable x_i is

1, if warehouse i is selected to be operating, 0 otherwise, for each warehouse $i \in I$. In addition, the decision variable s_{ik} represents the inventory level of medical supply k in warehouse i for all $i \in I$ and $k \in K$. The parameters of the first stage formulation are the warehouse operating costs g_i , the maximum amount available of each medical supply type e_k , and the storage capacity of warehouses for each medical supply type l_{ik} , for $i \in I$ and $k \in K$. The scenarios are denoted $\xi \in \Xi$ in the formulation.

The first stage of the SP model is given as:

$$\min \sum_{i \in I} g_i x_i + E_{\Xi}[Q(x, s, \xi)] \quad (1)$$

$$\text{s.t.} \quad \sum_{i \in I} s_{ik} \leq e_k \quad \text{for all } k \in K \quad (2)$$

$$s_{ik} \leq l_{ik} x_i \quad \text{for all } i \in I, k \in K \quad (3)$$

$$x_i \in \{0, 1\}, s_{ik} \geq 0 \quad \text{for all } i \in I, k \in K. \quad (4)$$

The objective function of the first stage (1) incorporates the total cost of operating warehouses in order to provide an incentive to execute the disaster preparedness at the lowest cost possible as well as the expected value of the second stage solution with respect to disaster scenarios, $E_{\Xi}[Q(x, s, \xi)]$. The objective function of the second stage is a function of the first stage actions, warehouse locations and inventory level decisions, and scenarios. It is explained next in the Stage 2 formulation. The limitations on the availability of medical supplies and capacities of warehouses are represented by (2) and (3) respectively.

Stage 2 - Transportation plans and demand satisfaction decisions

The second stage uses the index set J for hospitals in addition to those used in the first stage. The recourse decision variable in this stage is $t_{ijk}(\xi)$, which represents the amount of medical supply k to be delivered from warehouse i to hospital j under disaster scenario ξ . The parameter $r_{ij}(\xi)$ represents the transportation time between warehouse i and hospital j to reflect the road and traffic conditions related to the impact of disaster scenario ξ . In addition to minimizing the transportation durations, we penalize each unit of unfulfilled demand at hospital j of medical supply type k under scenario ξ by parameter $w_{jk}(\xi)$, and let the variable $y_{jk}(\xi)$ represent the amount of unfulfilled demand. Hence, the disaster managers have the liberty of prioritizing the significance of medical supply types for each hospital under different scenarios through the calibration of penalty parameters. We let $d_{jk}(\xi)$ represent the demand for medical supply type k at hospital j for scenario ξ . We use τ_{jk} to denote the upper limit for penalty of unsatisfied demands for each hospital j and medical supply type k .

The second stage of the SP is formulated as follows:

$$Q(x, s, \xi) = \min \sum_{i \in I} \sum_{j \in J} \left(r_{ij}(\xi) \sum_{k \in K} t_{ijk}(\xi) \right) + \sum_{j \in J} \sum_{k \in K} w_{jk}(\xi) y_{jk}(\xi) \quad (5)$$

$$\text{s.t.} \quad \sum_j t_{ijk}(\xi) \leq s_{ik} \quad \text{for all } i \in I, k \in K \quad (6)$$

$$\sum_i t_{ijk}(\xi) = d_{jk}(\xi) - y_{jk}(\xi) \quad \text{for all } j \in J, k \in K \quad (7)$$

$$w_{jk}(\xi) y_{jk}(\xi) \leq \tau_{jk} \quad \text{for all } j \in J, k \in K \quad (8)$$

$$t_{ijk}(\xi), y_{jk}(\xi) \geq 0 \quad \text{for all } i \in I, j \in J, k \in K. \quad (9)$$

The objective function of the second stage problem (5) includes the total transportation duration and the penalty of unfulfilled demand. The total amount of medical supplies that will be shipped

from a warehouse is bounded by the inventory levels of the corresponding warehouse for every supply type (6). Moreover, we add the balance constraint (7) to determine the unsatisfied demand amounts, $y_{jk}(\xi)$, and a non-negativity constraint for them to prevent favoring deliveries over the demand amounts. The constraint (8) ensures the total penalty for each hospital and medical supply type is smaller than a threshold value, τ_{jk} .

Consequently, the SP model provides the recommended warehouses x_i and their inventory levels s_{ik} as well as the required transportation amounts from warehouses to hospitals $t_{ijk}(\xi)$ for each disaster scenario.

3. Initial Transportation Plan

The SP model in Section 2 provides the optimal amounts of medical supplies to be transported from warehouses to hospitals under each scenario, i.e. $t_{ijk}(\xi)$. In order to dispatch vehicles based on the SP solution, we propose an MIP model that generates an initial transportation plan for the loading and routing problem of vehicles. We solve the MIP model for each scenario ξ to obtain the optimal vehicle loading and routing decisions taking $t_{ijk}(\xi)$ as an input.

Land transportation (e.g. trucks or vans) is assumed to be the only way of carrying supplies. Instead of contending with a classical vehicle routing problem, we propose a method that utilizes a set of predetermined routes at the expense of a preprocessing effort. With this intention, we define a *route* as an ordered list of a subset of hospitals with an initial warehouse. Furthermore, an adequate number of vehicles are assumed to be available at the warehouses at the onset of a disaster. In addition to the index sets I , J , and K , which are defined previously in the SP model, V and R denote the sets of available vehicles and possible routes, respectively. For notational purposes, we define the subsets R_{ij} of R , for $i \in I$ and $j \in J$ to include the routes that start at warehouse i and traverse hospital j . This notation allows us to easily represent routes from a single warehouse to several hospitals.

In the MIP model below, the binary decision variable z_{vr} enables the assignment of vehicle v to route r , for $v \in V$ and $r \in R$. The decision variable m_{ijkvr} denotes the transportation amount of k -type medical supply along the route r by vehicle v from warehouse i to hospital j . This determines a detailed loading and routing plan for each vehicle. The travel duration along route r is represented by parameter q_r . Furthermore, we separate the set of medical supply types into two disjoint types; types that require refrigeration ($l = 1$) and the ones that do not ($l = 2$). These sets are denoted by K_l for $l = 1$ and $l = 2$. Each vehicle v has a capacity of h_{vl} where l represents the classification of refrigeration capability.

The MIP model that provides a detailed transportation plan is presented:

$$\min \sum_{r \in R} q_r \left(\sum_{v \in V} z_{vr} \right) \tag{10}$$

s. t.

$$\sum_{i \in I} \sum_{j \in J} \sum_{k \in K_l} m_{ijkvr} \leq h_{vl} z_{vr} \quad \text{for all } v \in V, r \in R, l \in \{1, 2\} \tag{11}$$

$$\sum_{v \in V} \sum_{r \in R} m_{ijkvr} = t_{ijk}(\xi) \quad \text{for all } i \in I, j \in J, k \in K \tag{12}$$

$$\sum_{r \in R} z_{vr} \leq 1 \quad \text{for all } v \in V \tag{13}$$

$$m_{ijkvr} \leq 0 \quad \text{for all } i \in I, j \in J, k \in K, v \in V, r \notin R_{ij} \tag{14}$$

$$z_{vr} \in \{0, 1\}, m_{ijkvr} \geq 0 \quad \text{for all } i \in I, j \in J, k \in K, v \in V, r \in R. \tag{15}$$

The objective function (10) minimizes the total transportation duration of assigned vehicles. The capacity of vehicles are taken into account by constraint (11). For the disaster scenario ξ considered in the current run of this model, (12) assures that the distribution plan developed in the SP model,

$t_{ijk}(\xi)$, is attained. The necessity of assigning a vehicle to at most one route is guaranteed by (13). Finally, (14) prevents the loading of vehicle v to make a delivery from warehouse i to hospital j unless there is a route starting at i and traversing j .

4. Response Phase Transportation Model

The response to a disaster literally requires immediate reaction. The dynamic nature of some type of disasters necessitates continuous monitoring of the disaster zone and conducting relief efforts according to current disaster field information. We present a response phase MIP transportation model, similar to the MIP presented in Section 3, to optimize the distribution of medical supplies after the onset of the disaster. Different than the preparedness phase, we incorporate current disaster field information rather than probabilities. These updates include the demand at hospitals, the supply amounts in warehouses including possible resources in addition to the initial inventories, and the current transportation durations based on road and traffic conditions. In order to respond to the changes in the disaster zone and intervention capabilities of the command center, we presume that the response phase transportation model will be called repeatedly as the field information continues to be monitored.

This response phase transportation MIP uses the same index sets, I , J , K , V , and R as given in Section 3. In addition to the demand parameter d_{jk} , we include s_{ik} denoting the supply amount of medical supply k available in warehouse i . The decision variables of the model, z_{vr} and m_{ijkvr} , are the same as in Section 3 as well as the vehicle capacities, h_{lk} and route durations, q_r . We include y_{jk}^+ and y_{jk}^- to denote the extra amount of medical supply k delivered to hospital j on top of the demand and the amount of unsatisfied demand respectively. The response phase transportation model is formulated as follows:

$$\min \sum_{r \in R} q_r \left(\sum_{i \in I} \sum_{j \in J} \sum_{k \in K} \sum_{v \in V} m_{ijkvr} \right) + M \sum_{j \in J} \sum_{k \in K} y_{jk}^- + \sum_{v \in V} \sum_{r \in R} z_{vr} \quad (16)$$

$$\text{s.t.} \quad \sum_{j \in J} \sum_{v \in V} \sum_{r \in R} m_{ijkvr} \leq s_{ik} \quad \text{for all } i \in I, k \in K \quad (17)$$

$$\sum_{i \in I} \sum_{v \in V} \sum_{r \in R} m_{ijkvr} - y_{jk}^+ + y_{jk}^- = d_{jk} \quad \text{for all } j \in J, k \in K \quad (18)$$

$$\sum_{i \in I} \sum_{j \in J} \sum_{k \in K_l} m_{ijkvr} \leq h_{vl} z_{vr} \quad \text{for all } v \in V, r \in R, l \in \{1, 2\} \quad (19)$$

$$\sum_{r \in R} z_{vr} \leq 1 \quad \text{for all } v \in V \quad (20)$$

$$m_{ijkvr} \leq 0 \quad \text{for all } i \in I, j \in J, k \in K, v \in V, r \notin R_{ij} \quad (21)$$

$$z_{vr} \in \{0, 1\}, m_{ijkvr} \geq 0, y_{jk}^+ \geq 0, y_{jk}^- \geq 0 \quad \text{for all } i \in I, j \in J, k \in K, v \in V, r \in R. \quad (22)$$

As a variation from the MIP model in Section 3, the objective function (16) is composed of three terms. The first term is the sum of load amounts weighted by the route durations, which accelerates the delivery of higher demand amounts over longer distances. The second term in the objective function includes the necessity of satisfying as much demand as possible by using a large positive penalty coefficient M . The third term is the summation of vehicle assignment variables, z_{vr} , to prevent the unnecessary assignment of vehicles to routes.

The constraints on supplies is given in (17). The balance constraint in (18) declares the relationship between deliveries and demand amounts, allowing for excess amount in deliveries y_{jk}^+ , and unsatisfied demand y_{jk}^- . Both (19) and (20) are the same as in the vehicle assignments model given in Section 3.

Table 1 Probabilities of Scenarios

Scenario	Seattle Fault			Cascadia Fault		
	W	R	N	W	R	N
Probability	0.11	0.07	0.22	0.17	0.11	0.32

5. Case Study: Potential Earthquakes in Seattle

We present a case study to prepare for earthquakes in the Seattle area with regard to medical supply storage and distribution to hospitals. Two earthquakes are expected; the Seattle Fault with magnitude 6.0, and the Cascadia Fault with magnitude 9.0. Under these scenarios, damage to homes, warehouses, and buildings is expected throughout the region. Major highways will experience substantial damage, partial closures, and collapsed bridges (Stewart 2005) which will cause longer transportation durations. The I-5/Highway 99 corridor, which is heavily traveled in the Seattle area, is likely to be damaged. Significant disruption of utilities and damage to tall buildings in the downtown area are expected (CREW 2005).

For the case study, we assume that the relative probabilities of Seattle Fault and Cascadia Fault earthquakes are 0.4 and 0.6 respectively. The pattern of the effects of the earthquakes in the city changes by the breaking fault and occurrence time of the event. We expect that the Seattle Fault earthquake will damage the southern part of the city and I-5, whereas the Cascadia Fault earthquake will cause disruptions in the northern part and smaller bridges of the city. We divide the time of day into three periods: working hours (W), rush hours (R), and non-working hours (N). Thus, we have six disaster scenarios in this case. For the weekdays, we assume that there are 8 working, 5 rush and 9 non-working hours. We treat Saturdays as weekdays and Sundays as non-working time. Thus, 168 hours in a week are divided into 48 working hours, 30 rush hours and 90 non-working hours. The probabilities of the six scenarios are given in Table 1.

In this case study, we consider ten hospitals and medical centers, given without their real names, in Table 2. Although our models can cover several types of medical supplies, in this case study we consider a single type of medical supply for the sake of clarity in the representation. Table 2 also includes estimated demand amounts for each hospital, using the predicted damage and population density in each scenario.

In estimation of demand of hospitals, we consider the fact that downtown Seattle has a higher population during working hours, whereas residential areas are more populated in non-working hours. Thus, we assigned relatively higher demand to downtown hospitals during working hours for the Seattle Fault earthquake. Demand in hospitals near residential areas is increased during non-working hours for the Cascadia Fault, which is more likely to affect the northern part of Seattle. We assume that the demand of hospitals is balanced in different parts of the city in rush hours. We assigned a large fixed value as a penalty coefficient for unsatisfied demand in the objective function to provide an incentive to satisfy the demand of hospitals with equal importance. The total availability of medical supplies is assumed to be sufficient for all scenarios.

The medical supplies are either stored in hospital-owned or private warehouses. We list five possible warehouse buildings in Table 3, with their capacities and operating costs (denoted l_{ik} and g_i respectively in the first stage of SP formulation). The cost/capacity ratio is included as an additional measure to characterize each warehouse. The locations of the hospitals and warehouses are marked on the map given in Figure 2. In this case study, we allow twenty identical vehicles with capacity 7,000 units, and locate 5 vehicles each at warehouses 1, 2, and 3; 3 vehicles at warehouse 4 and 2 vehicles at warehouse 5. We only consider 2 vehicles at warehouse 5 because the warehouse is relatively small, and the capacity of one vehicle exceeds the capacity of the warehouse. Two vehicles allows warehouse 5 to deliver supplies along two different routes.

The transportation durations for each scenario are determined by considering the effect of fault breaks on the roads and highways given above. We take the normal and rush hour transportation

Table 2 Demand Amounts of Hospitals

Hospital	Seattle Fault			Cascadia Fault		
	W	R	N	W	R	N
1	6313	6042	9491	9234	8306	13624
2	3409	3857	3994	5296	3958	7149
3	4969	3732	6466	5922	5147	9357
4	1532	3454	4254	5422	7114	7507
5	2293	3487	4836	7185	8750	10258
6	3129	2508	2913	3801	1814	2112
7	10021	5932	3869	12410	6830	7639
8	7342	4617	4213	9134	3803	5924
9	5723	3686	1773	6784	4036	4382
10	5214	3498	2189	6048	3006	3861

Table 3 Warehouse Capacities and Operating Costs

Warehouse	Capacity (10^3 units)	Cost ($\$10^6$)	Cost/Capacity ($\$10^3$ /unit)
1	20	25	1.25
2	25	20	0.80
3	30	12	0.40
4	10	6	0.60
5	5	12	2.40

Table 4 Transportation Duration Coefficients

Path type	Seattle Fault			Cascadia Fault		
	W	R	N	W	R	N
Paths through I-5	7	7	4	4	3	1
Paths through small bridges	4	3	1	7	7	4
North paths	2	2	1	3	3	2
South paths	3	3	2	2	2	1

durations and multiply by the coefficients (Table 4) determined according to time and the broken fault to calculate the transportation durations among warehouses and hospitals. We determine 90 routes, each starting at a warehouse and traversing a sequence of hospitals, depending on their locations in the city, as explained in Section 3. The route durations are given in Table 5.

The SP model is applied to the case study described above. The solution of the SP model is achieved by solving the deterministic equivalent of the model, which allows us to compute the optimal first-stage decision when the second-stage can be represented in a closed form, which is given by the expectation of the second stage objective given in (5). Although there are more efficient SP algorithms in the literature, this was sufficient for our case study. We coded our models in GAMS and solved by CPLEX solver in less than one minute for both SP and MIP solutions.

The solution of the SP model is then input into the vehicle assignments model for each earthquake scenario. According to the optimal solution, the first three warehouses are selected to actively store medical supplies in preparation for the possible earthquakes. The detailed results are presented in Table 6, which shows the transportation amounts on the routes from warehouses to hospitals. In some scenarios, two vehicles are needed to cover the same route, for example, from Warehouse 2 to Hospital 1. The totals indicate the amount of supplies needed to store at each warehouse by scenario. In this case study, the demand at all hospitals are satisfied for all earthquake scenarios.

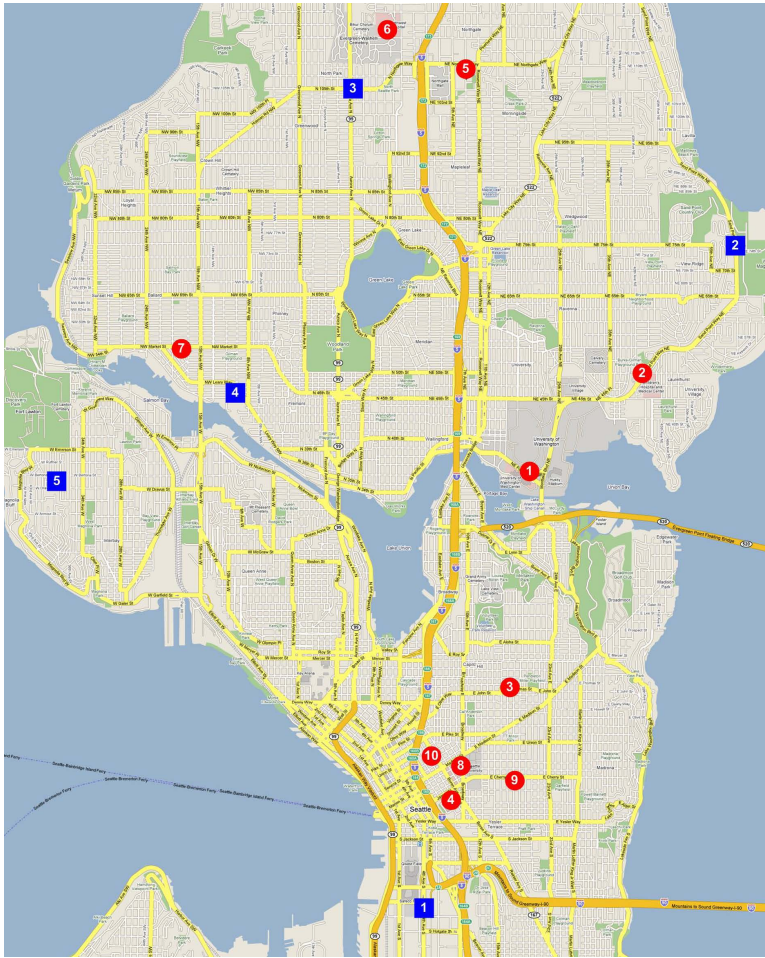


Figure 2 Seattle map: Hospitals and possible warehouses

For the Cascadia Fault non-working time scenario, the inventory levels of the three warehouses are 20,000, 21,813, and 30,000.

The major factors in warehouse selection are the operating cost, the capacity and the distance to the hospitals. In the given case, the selected warehouses, 1, 2, and 3, are the ones with low cost/capacity ratios except warehouse 1, which is significantly closer to the downtown hospitals. The selected warehouses serve the hospital closest to them as long as their material supplies are sufficient. On the average with respect to scenarios, 7.3 out of 10 hospitals are served by single warehouses. When a warehouse has a material shortage to serve the closest hospitals, the second closest one is assigned to serve them.

As one possible summary of the detailed results, the number of utilized vehicles for each scenario is given in Table 7. We observe from Table 7 that the total number of vehicles utilized is at most 13, which is required for two of Cascadia Fault earthquake scenarios, however four of the scenarios require 10 or less vehicles. Also, if we total the maximum needed at each warehouse, we obtain 14 vehicles. To decide the number of vehicles to have available, we first observe that warehouse 1 utilizes four of its vehicles in five of the six scenarios. Thus, the fifth one may be unnecessary. Warehouse 2 uses two vehicles for Seattle Fault scenarios, but up to five for Cascadia Fault scenarios. There is a similar situation for warehouse 3. In addition, Table 7 presents the expected number of vehicles to be utilized for each hospital calculated by using the probabilities of scenarios given in Table 1. This information can provide insight in determining the ideal number

Table 5 Routes, Visited Hospitals and Transportation Durations for Scenarios

Wareh.	Hospital	Seattle Fault			Cascadia Fault			Wareh.	Hospital	Seattle Fault			Cascadia Fault		
		W	R	N	W	R	N			W	R	N	W	R	N
1	1	77	210	44	44	90	11	3	10	15	15	10	10	10	5
1	2	105	210	60	60	90	15	3	2-1	126	189	71	85	96	30
1	3	27	27	18	18	18	9	3	6-5	18	18	9	27	27	18
1	4	15	15	10	10	10	5	3	10-4	24	24	16	16	16	8
1	5	105	210	60	60	90	15	3	3-1-2	216	380	90	246	420	120
1	6	112	210	64	64	90	16	3	6-5-7	46	46	23	69	69	46
1	7	147	245	84	84	105	21	3	7-1-2	88	108	44	132	162	88
1	8	18	18	12	12	12	6	3	2-1-3-9	309	474	155	265	361	111
1	9	24	24	16	16	16	8	3	4-9-8-10	125	272	74	74	123	23
1	10	18	18	12	12	12	6	4	1	24	24	12	36	36	24
1	1-2	89	222	50	62	108	23	4	2	34	50	17	51	75	34
1	9-3	42	42	28	28	28	14	4	3	119	119	68	68	51	17
1	1-5-6	252	469	144	144	201	36	4	4	119	119	68	68	51	17
1	4-8-10	30	30	20	20	20	10	4	5	34	34	17	51	51	34
1	4-10-3	45	45	30	30	30	15	4	6	30	50	15	45	75	30
1	5-6-7	151	256	83	129	159	61	4	7	40	70	20	60	105	40
1	7-2-1	211	329	116	180	231	85	4	8	54	90	36	36	60	18
1	4-8-10-9-3	63	63	42	42	42	21	4	9	57	105	38	38	70	19
2	1	25	25	11	39	39	25	4	10	51	51	34	34	34	17
2	2	14	14	7	21	21	14	4	1-2	36	36	18	54	54	36
2	3	133	133	76	76	57	19	4	3-9	137	137	80	80	63	23
2	4	126	245	72	72	105	18	4	5-6	46	46	23	69	69	46
2	5	26	26	13	39	39	26	4	7-6	90	134	46	135	204	90
2	6	32	50	16	48	75	32	4	7-6-5	100	148	50	150	222	100
2	7	42	60	21	63	90	42	4	1-2-5-6	211	295	118	154	165	61
2	8	133	245	76	76	105	19	4	4-9-8-10	146	146	86	86	69	26
2	9	140	245	80	80	105	20	4	10-4-9-8-3	102	102	68	68	68	34
2	10	119	245	68	68	105	17	5	1	147	210	84	84	90	21
2	2-1	28	28	14	42	42	28	5	2	56	56	28	84	84	56
2	5-6	38	38	19	57	57	38	5	3	154	154	88	88	66	22
2	10-4	128	254	74	74	111	20	5	4	66	66	44	44	44	22
2	7-6-5	102	138	51	153	207	102	5	5	108	81	27	189	189	108
2	2-1-10-4	238	448	134	162	222	58	5	6	96	72	24	168	168	96
2	4-9-8-10	153	272	90	90	123	27	5	7	48	36	12	84	84	48
2	2-1-3-9-8-4-10	533	943	282	406	577	155	5	8	69	69	46	46	46	23
2	2-1-10-4-8-9-3	533	943	282	406	577	155	5	9	75	75	50	50	50	25
3	1	98	245	56	56	105	14	5	10	63	90	42	42	60	21
3	2	112	175	64	64	75	16	5	1-2	159	222	90	102	108	33
3	3	112	245	64	64	105	16	5	3-9	172	172	100	100	78	28
3	4	98	245	56	56	105	14	5	5-6	120	93	33	207	207	120
3	5	14	14	7	21	21	14	5	7-2-1	112	120	44	180	210	112
3	6	8	8	4	12	12	8	5	7-5-6	108	114	42	174	201	108
3	7	24	24	12	36	36	24	5	1-2-5-6	334	481	190	202	219	58
3	8	45	105	30	30	70	15	5	10-8-9-4	96	123	64	64	82	32
3	9	51	105	34	34	70	17	5	10-4-8-9-3	114	141	76	76	94	38

to be reserved for emergency. For instance, we can conclude that warehouse 1 should have four vehicles on duty which are all needed in five of the six scenarios. We recommend that warehouse 2 and 3 each have four vehicles on duty. This happens to be the allocation of vehicles under the Cascadia Fault working hours scenario, and is sufficient to meet five of the six scenarios. In the event of the Cascadia Fault non-working time scenario, one of the vehicles at warehouse can be reallocated to warehouse 2. Thus the results can be useful to a planning team to assist with disaster preparedness.

6. Conclusions

We modeled the preparation and response phases of disaster management in terms of medical supply distribution with stochastic programming and MIP and illustrated the methodology on a case of earthquake preparation for the Seattle area. Our methodology consists of two steps. First, we determine the aggregate transportation amounts from warehouses to hospitals by an SP

Table 6 Visited Hospitals and Transportation Amounts

Whs.	Hosp.	Seattle Fault			Cascadia Fault		
		W	R	N	W	R	N
1	3	4,969	3,732	6,466	5,922	5,047	
	4		3,454	4,254	5,422	3,917	6,431
	8	1,874	4,617	4,213	1,872		
	9	5,723	3,686	1,773	6,784	4,036	
	9-3						4,382-2,187
	4-8-10	1,532-5,468-0				3,197-3,803-0	1,076-5,924-0
	Total	19,566	15,489	16,706	20,000	20,000	20,000
2	1	6,313	6,042	6,485	7,000	5,264	7,000
	1				2,234		
	2	3,409	3,857		5,296		7,000
	3					100	7,000
	3						170
	5				6,706		
	2-1			3,994-3,006		3,958-3,042	149-494
	Total	9,722	9,899	13,485	21,236	12,364	21,813
3	1						6,130
	5			4,836		3,564	7,000
	6			2,913			
	7	7,000	5,932	3,869	7,000	6,830	7,000
	7	3,021			5,410		
	8				6,310		
	10	5,214	3,498	2,189		3,006	3,861
	6-5	3,129-2,293	2,508-3,487		3,801-479	1,814-5,186	
	6-5-7						2,112-3,258-639
	4-9-8-10				0-0-952-6,048		
Total	20,657	15,425	13,807	30,000	20,400	30,000	

Table 7 Number of Vehicles Assigned

Warehouse	Seattle Fault			Cascadia Fault			Maximum	Expected
	W	R	N	W	R	N		
1	4	4	4	4	4	3	4	3.68
2	2	2	2	4	3	5	5	3.41
3	4	3	4	5	3	5	5	4.31
Total	10	7	10	13	10	13		11.40

model and then conduct the vehicle assignments by an MIP model. This decomposition provided a significant reduction in the problem size, as well as the solution time and memory requirements.

The MIP problem that we solve by the vehicle assignments model is a capacitated vehicle routing problem (CVRP), which is challenging to solve due to long CPU time and the large memory requirements. However, it is straightforward to define possible routes that the vehicles might traverse in the city. Hence, to solve this problem we took advantage of selecting among predetermined routes at the expense of preprocessing of routes. Consequently, we solve the CVRP problem in a short time.

A similar CVRP problem is solved for the response phase of the medical supply distribution. The response phase model differs from the vehicle assignments model, in that both the supply and demand amounts are parameterized to achieve a continuous monitoring of the disaster region and making transportation decisions.

In summary, we offer a stochastic optimization approach to the medical supply distribution in the preparedness and response phases of disaster management, specifically possible earthquakes in Seattle area. Our method takes the advantage of a two-step approach combining SP and MIP for the preparedness phase, and utilizes a modified MIP for the response phase. For both phases, we provide a solution for the Seattle area in a reasonable solution time for a humanitarian operation.

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