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Stochastic optimization of medical supply location and distribution in disaster management

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ABSTRACT

We propose a stochastic optimization approach for the storage and distribution problem of medical supplies to be used for disaster management under a 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. A benefit of this approach is that the subproblem can be used to suggest loading and routing of vehicles to transport medical supplies for disaster response, given the evaluation of up-to-date disaster field information. We present a case study of our stochastic optimization approach for disaster planning for earthquake scenarios in the Seattle area. Our modeling approach can aid interdisciplinary agencies to both prepare and respond to disasters by considering the risk in an efficient manner.

1. Introduction

Decisions to support preparedness 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 a stochastic program 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. 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 considering the timely delivery of medical supplies in the event of an earthquake. 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. A subproblem in our stochastic programming model creates alternative transportation plans, including number of vehicles and routes, to deliver the medical supplies from their storage locations to the hospitals.

Our stochastic program provides a decision-making model for the disaster planning team for both preparedness and response phases of the disaster management process focused on distribution of medical supplies, as summarized in Fig. 1. We develop a two-stage stochastic programming (SP) model to be used in the preparedness phase, which recommends 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. During the second stage of the SP model, the amount of medical supplies to be delivered to hospitals is determined for each scenario at an aggregated level. This aggregated decision is converted to detailed vehicle assignments and routing for each scenario in a mixed-integer programming (MIP) model which provides an emergency transportation plan with the number of vehicles to be available at each warehouse, as well as a few preplanned routes. The same MIP model can also be used during response phase after an earthquake, with updated information on road conditions, the need for medical supplies, and the availability of medical supplies to provide a revised transportation plan with detailed routes relatively quickly.

The rest of the article is organized as follows. Section 2 provides a review of disaster management literature with

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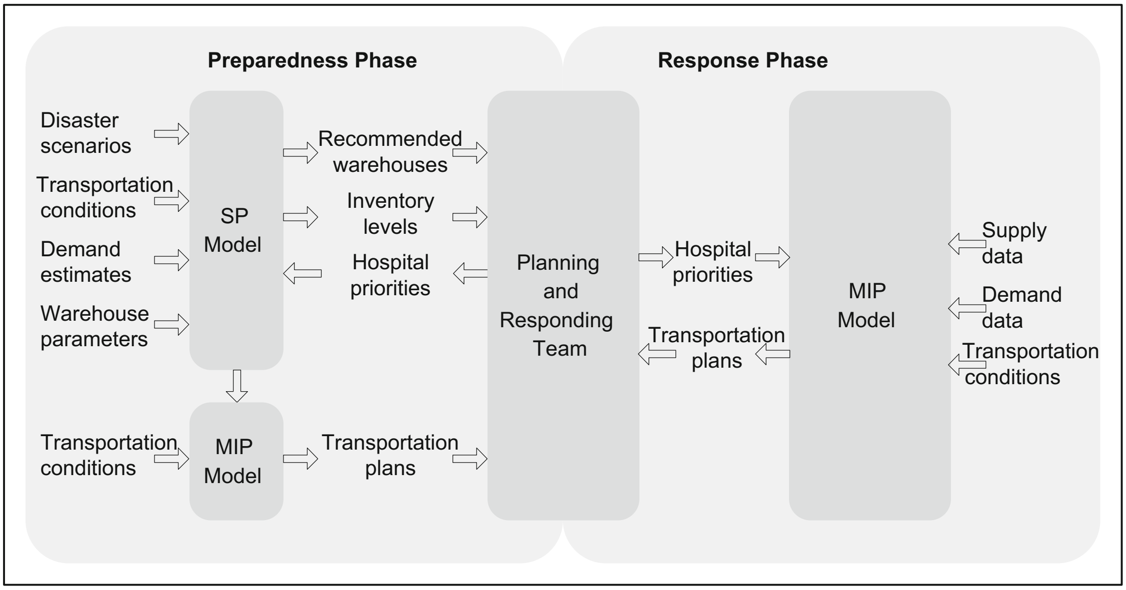

Fig. 1. Information flow between optimization models and command center in disaster management.

stochastic aspects. In Section 3, we present our two-stage SP model for warehouse selection and storage of medical supplies for disaster preparedness. The MIP model that converts the solution of the SP subproblem to vehicle assignments and routing is in Section 4. In Section 5, we present a case study for potential earthquakes in the Seattle area. We discuss the practical implementation issues of our approach in Section 6. Finally, we provide our conclusions and observations in Section 7.

2. Literature review

We review the disaster management literature by first discussing several studies on the location of emergency supplies using deterministic and probabilistic approaches and second focusing on managing the uncertainty in disaster preparedness using a scenario-based approach including stochastic programming.

Brotcorne et al. (2003) classify the location and assignment of ambulances and other emergency vehicles into three model types: deterministic models, probabilistic queueing models, and dynamic models. Jia et al. (2007a) review deterministic and probabilistic facility location models used to model smaller scale emergencies and they introduce three deterministic models: a covering model providing a coverage of demand points within a distance limit, a deterministic $P-$median model minimizing the total distance between demands and facilities, and a $P-$center model optimizing the worst performance of the system by minimizing the maximum distance between any demand point and its nearest service center. Furthermore, Jia et al. (2007b) propose heuristic solution approaches for facility location of medical supplies for large-scale emergencies. They address demand uncertainty and insufficiencies of medical supplies by requiring multiple supply points. For a similar setting in relief operations, Tzeng et al. (2007) provide a multi-criteria deterministic model to distribute commodities to disaster areas considering the cost, service time and demand satisfaction.

Determining the minimum number of ambulances and their locations is another aspect of emergency management studied by Alsalloum and Rand (2006) and Rajagopalan et al. (2008). The former uses goal programming for locating vehicles to maximize the coverage of expected demand while minimizing the number of vehicles, 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 using probabilistic demand, they use demand forecasts of future periods in their multi-period setting. 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 by Iakovou et al. (1996).

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 (Barbarosoglu and Arda, 2004; Beraldi et al., 2004; Chang et al., 2007; Cormican et al., 1998; Lamiri et al., 2006; Morton et al., 2007; Pan et al., 2003). Disaster management has a two-stage nature: choosing the level of preparedness (e.g. location and inventory level of medical supplies) before the disaster occurs, and then reacting once the uncertainty has been revealed. In disaster management, using a scenario approach has both advantages and disadvantages as discussed in Snyder (2006). An advantage is the ability to allow parameters to be statistically dependent, which is a realistic characteristic, and to consider specific future events (Snyder, 2006). A disadvantage is that scenarios limit the number of possible states, however Snyder (2006) also remarks that "the scenario approaches generally results in more tractable models." Barbarosoglu and Arda (2004) utilize a scenario-based two-stage SP model for transportation planning in earthquake response, where they seek optimal transportation plans. They 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 later response given impact scenarios that are more detailed branches of the earthquake scenarios.

Beraldi and co-authors (Beraldi and Bruni, 2009; Beraldi et al., 2004) address the location and assignment of emergency vehicles. In Beraldi et al. (2004), they use a mixed integer formulation with probabilistic constraints to solve for the location and assignment of emergency vehicles. In Beraldi and Bruni (2009), they formulate a two-stage stochastic program. Beraldi et al. (2004) assume the random vehicle requests are independent, whereas Beraldi and Bruni (2009) drop this simplifying assumption and allow spatial dependence of vehicle requests in the SP model. The problem of locating and distributing rescue resources for flood emergency is studied by Chang et al. (2007) under possible flood scenarios with a two-stage stochastic programming model.

We propose a methodology to solve the storage and distribution problem of emergency medical supplies. In the Seattle area, the regional hospitals must develop emergency plans for coordination of medical supply inventory and storage locations. This problem has similar characteristics to the location and assignment of emergency vehicles studied in Beraldi and Bruni (2009), Beraldi et al. (2004), and Chang et al. (2007), however it has some significant differences. In contrast to Beraldi and Bruni (2009), Beraldi et al. (2004), and Chang et al. (2007), where the location and amount of demand is the main source of randomness, our problem has randomness in the location and amount of demand, and in the available transportation routes and transportation times. This leads to different types of scenarios where the transportation routes and times are directly related to the location and amount of demand. This statistical dependence leads to our use of the scenario approach. We consider two stages, where one corresponds to the preparedness phase and the other corresponds to the response phase. This differs from the treatment of stages in Barbarosoglu and Arda (2004), Beraldi et al. (2004), and Chang et al. (2007). Our objective is to minimize the transportation duration (transportation times weighted by the amount) and minimize unsatisfied demand, recognizing it may be impossible to satisfy demand under all scenarios. However, we add a constraint to limit the total penalties incurred from unsatisfied demand. We use penalty coefficients to capture time delays and increased costs in obtaining medical supplies from facilities outside of the Seattle area. Although the problems introduced in Brotcorne et al. (2003) and Jia et al. (2007a, 2007b) have similarities (i.e. uncertain demand), our emergency supply transportation problem needs to address simultaneous multiple demand locations whereas the ambulance routing problem focuses on individual demand points.

In scenario based modeling of the disaster management process, the identification of scenarios and assigning probabilities are difficult tasks (Snyder, 2006) and their parameters are of critical importance. Although there are applications that present ways of selecting disaster scenarios in the literature (Jenkins, 2000), we rely on technical disaster experts to determine our earthquake scenarios; specifically the Department of Earth and Space Sciences at the University of Washington. The Cascadia fault (Cascadia subduction zone) (CREW, 2005) and the Seattle fault (Stewart, 2005) earthquakes are the two main disasters threatening the Seattle area. 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 times in the city. 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 distinguish working hours, rush hours and non-working hours for both earthquakes, as described in Section 5.

3. Stochastic programming approach for disaster preparedness

A two-stage SP model is proposed for the medical supply storage and distribution problem at a city level. The optimal policy from our SP model is a single pre-event policy of warehouse selections and inventory levels from the first stage and a collection of recourse decisions defining transportation plans from the second stage, in response to each disaster scenario. The transportation plans provided by the SP model are aggregated plans. To convert them to a detailed optimal routing plan of vehicles as well as their load amounts for each scenario, we developed an MIP model (discussed in Section 4). 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 each warehouse 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

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

$$\text{subject to} \quad \sum_{i \in I} s_{ik} \le e_k \quad \text{for all } k \in K \tag{2}$$

$$s_{ik} \le l_{ik} x_i \quad \text{for all } i \in I,\ k \in K \tag{3}$$

$$x_i \in \{0,1\},\ s_{ik} \ge 0 \quad \text{for all } i \in I,\ k \in K \tag{4}$$

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 action (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 $c_{ij}(\xi)$ 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. We use the term transportation duration to mean transportation times weighted by transportation amounts. We minimize the total transportation duration in the second stage to benefit delivering a lot of medical supplies quickly, even though a few supplies may take a long time. In addition, 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:

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

$$\text{subject to} \quad \sum_j t_{ijk}(\xi) \le s_{ik} \quad \text{for all} \quad i \in I, \; k \in K \tag{6}$$

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

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

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

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, $y_{jk}(\xi)$. 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.

4. Transportation plan

The second stage of the SP model in Section 3 is a subproblem that 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 provide an MIP model that converts $t_{ijk}(\xi)$ to an optimal transportation plan for the loading and routing problem of vehicles for each scenario.

Land transportation (e.g. trucks or vans) is assumed to be the only way of distributing medical 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. This is a realistic approach because there is already a daily transportation plan from warehouses to hospitals and we expand the existing routes with a few alternative routes that avoid bridges and highways that are vulnerable to earthquakes. 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 time along route r is represented by parameter q_r. Note that the route time q_r is not the sum of $c_{ij}(\xi)$ because the route r may include several hospitals whereas $c_{ij}(\xi)$ includes exactly one hospital. The more detailed route time for q_r is needed for the transportation plan, while $c_{ij}(\xi)$ is an approximation used for the higher level transportation amounts in the SP formulation. 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 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

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

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

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

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

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

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

The objective function (10) minimizes the total transportation time 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.

5. Case study: potential earthquakes in Seattle

We present a case study to demonstrate our approach to prepare for earthquakes with regard to inventory levels of medical supplies at warehouses and predetermined routes and transportation plans to deliver the medical supplies to hospitals in the Seattle area. It is based on discussions with an Emergency Management Coordinator of a large Seattle medical center. Although our model 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.

The Seattle area is expected to have earthquakes triggered by two faults: the Seattle fault and the Cascadia fault, with magnitudes 6.7 and 9.0 respectively. These projections are determined according to earthquake research using statistical analyses on both the causes of disasters and historical disaster data (CREW, 2005; Stewart, 2005). 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). 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). In our stochastic programming approach, we utilize these two most probable earthquake scenarios that are developed in detail by earthquake scientists.

Based on the impact of both types of earthquakes, and population densities around hospitals, we estimate the need for medical supplies in different parts of the city and at different times of the day. We assume 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 create six disaster scenarios as given in Table 1. For Monday through Saturday, we assume that there are 8 working, 5 rush and 11 non-working hours. We treat Sundays as non-working time. Thus, 168 h in a week are divided into 48 working hours, 30 rush hours and 90 non-working hours. We assume that the relative probabilities of Seattle fault and Cascadia fault earthquakes are 0.4 and 0.6, respectively, which yields the probabilities of the six scenarios given in Table 1.

In this case study, we consider ten hospitals and medical centers in Seattle, given without their real names, in Table 2. Table 2 also includes estimated demand amounts for each hospital, using the predicted damage and population density in each scenario. To estimate the demand at 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. It is expected that people will go to their nearest hospital in the event of a disaster. 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 is balanced in different parts of the city in rush hours.

We consider five possible warehouses in Table 3, with their capacities and operating costs (denoted l_{ik} and g_i, respectively in the first stage of the 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 Fig. 2. In this case study, we allow 20 identical vehicles with capacity 7000 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 times for each scenario are determined by considering the effect of fault breaks on major roads and highways. We take the normal and rush hour transportation times and multiply by the coefficients (Table 4) determined according to scenario to calculate the transportation times 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 4. The times for each route are given in Table 5.

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

Table 2
Demand amounts of hospitals.

Hospital	Seattle fault			Cascadia fault		
	W	R	N	W	R	N
1	6313	6042	9491	9234	8306	13,624
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	10,258
6	3129	2508	2913	3801	1814	2112
7	10,021	5932	3869	12,410	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

The optimal solution to the SP model selects the first three warehouses to actively store medical supplies in preparation for the possible earthquakes. The MIP model uses the SP second stage solution to determine vehicle assignments and routes for each earthquake scenario. The detailed results are presented in Table 6, which shows the transportation amounts on the routes from warehouses to hospitals. In this case study, the demand at all hospitals is satisfied for all earthquake scenarios.

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 are 1, 2, and 3. Although warehouse 1 has the second highest cost/capacity ratio, it is significantly closer to the downtown hospitals. Warehouse 3 has the lowest cost/capacity ratio and is conveniently located in north Seattle in a residential neighborhood near two hospitals. Although warehouse 4 has the second lowest cost/capacity ratio, it is not selected due to its location. To serve the downtown hospitals 3, 4, 8, 9, and 10, transportation routes from warehouse 4 involve bridges and are relatively long. Transportation times from warehouse 4 to the north end hospitals (1, 2, 5, and 6) are also relatively long. Consequently, warehouse 2 with a middle cost/capacity ratio, is selected. It provides a better location with regards to more hospitals.

The selected warehouses (1, 2, 3) serve the hospital closest to them (4, 2, and 6, respectively) 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. For example, warehouse 1 serves the cluster of downtown hospitals 3, 4, 8, 9, and 10. Under some scenarios, warehouse 2 provides additional supplies to hospital 3 and warehouse 3 supplements hospitals 8, 9, and 10 (see Table 6). 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. For the Cascadia fault non-working time scenario, the inventory levels of the three warehouses are 20,000, 21,813, and 30,000.

As another 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 the 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

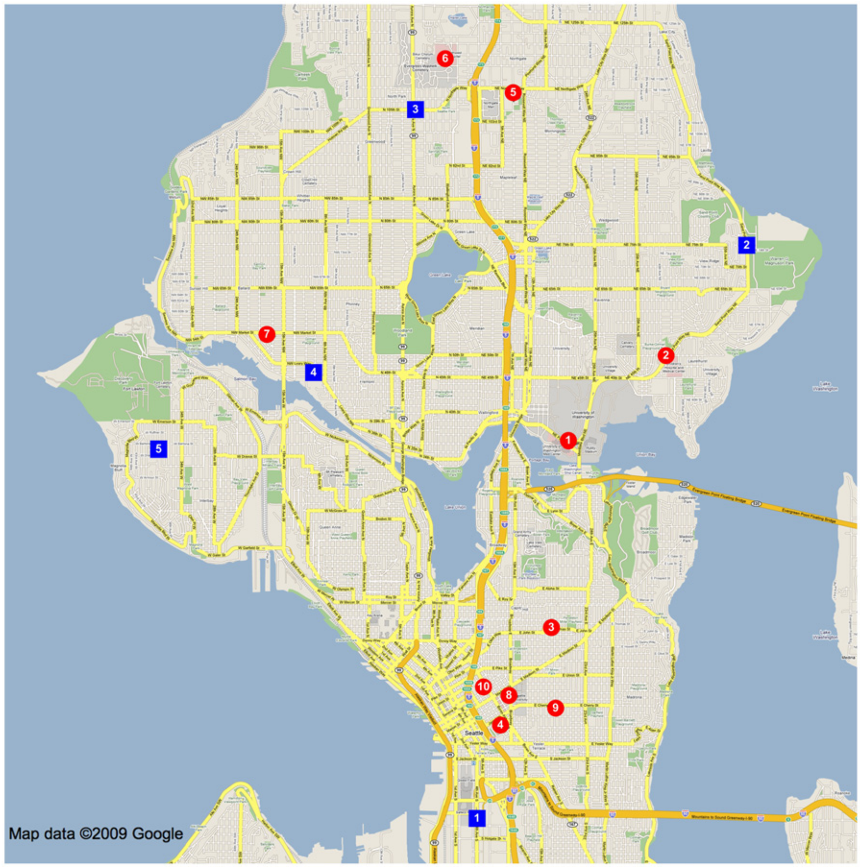

Fig. 2. Seattle map: hospitals and possible warehouses.

Table 4
Transportation time 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

given in Table 1. This information can provide insight in determining the ideal number 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 warehouses 2 and 3 each have four vehicles on duty. This happens to be the assignment 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. Practical implementation

Although our case study highlights earthquakes in Seattle, our methodology is capable of providing robust preparedness plans for many types of disasters in different cities. However, the data has to be provided by the various stakeholders of disaster management and hospitals. The disaster scenarios should be prepared by disaster scientists and transformed to predict damages in different parts of the city. The impact of the disaster scenarios must be transformed to the need for medical supplies in hospitals and impact on transportation routes and times. The medical emergency personnel must contribute by identifying the demand of medical supplies according to the type and prioritization of medical supply types through penalty parameters of unsatisfied demand. The availability of medical supply types, possible warehouse locations, capacities and operating costs need to be determined in advance. We also need the frequently used routes from warehouses to hospitals as well as alternative routes according to the possible damages to transportation infrastructure.

We solve the SP model using the deterministic equivalent of the model. Although there are more efficient SP algorithms in the literature, this was sufficient for our case study. We coded our models in GAMS and used the CPLEX solver on a PC with 1.8 GHz processor. All the runs solved in less than 1 min for both the SP and MIP models. The case study includes a reasonable numbers of hospitals and warehouses however we only consider a single medical supply type. Our discussion with emergency experts reveals that there are 6–10 major medical supply types to be considered. Even with 10 medical supply types, the models can be solved in a reasonable time for disaster preparedness. In our decision models, we first determine the aggregate transportation amounts from warehouses to hospitals by the SP 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 computation time and memory requirements.

Table 5
Routes, visited hospitals and transportation times for scenarios.

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

Table 5 (*continued*)

Warehouse	Hospital	Seattle fault			Cascadia fault		
		W	R	N	W	R	N
5	**2**	56	56	28	84	84	56
5	**3**	154	154	88	88	66	22
5	**4**	66	66	44	44	44	22
5	**5**	108	81	27	189	189	108
5	**6**	96	72	24	168	168	96
5	**7**	48	36	12	84	84	48
5	**8**	69	69	46	46	46	23
5	**9**	75	75	50	50	50	25
5	**10**	63	90	42	42	60	21
5	**1–2**	159	222	90	102	108	33
5	**3–9**	172	172	100	100	78	28
5	**5–6**	120	93	33	207	207	120
5	**7–2–1**	112	120	44	180	210	112
5	**7–5–6**	108	114	42	174	201	108
5	**1–2–5–6**	334	481	190	202	219	58
5	**10–8–9–4**	96	123	64	64	82	32
5	**10–4–8–9–3**	114	141	76	76	94	38

Table 6
Visited hospitals and transportation amounts.

Warehouse	Hospital	Seattle fault			Cascadia fault		
		W	R	N	W	R	N
1	**3**	4969	3732	6466	5922	5047	
	4		3454	4254	5422	3917	6431
	8	1874	4617	4213	1872		
	9	5723	3686	1773	6784	4036	
	9–3						4382–2187
	4–8–10	1532–5468-0				3197–3803-0	1076–5924-0
	Total	**19,566**	**15,489**	**16,706**	**20,000**	**20,000**	**20,000**
2	**1**	6313	6042	6485	7000	5264	7000
	1				2234		
	2	3409	3857		5296		7000
	3					100	7000
	3						170
	5				6706		
	2–1			3994–3006		3958-3042	149–494
	Total	**9722**	**9899**	**13,485**	**21,236**	**12,364**	**21,813**
3	**1**						6130
	5			4836		3564	7000
	6			2913			
	7	7000	5932	3869	7000	6830	7000
	7	3021			5410		
	8				6310		
	10	5214	3498	2189		3006	3861
	6–5	3129–2293	2508–3487		3801–479	1814–5186	
	6–5–7						2112–3258–639
	4–9–8–10				0–0–952–6048		
	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

Furthermore, our vehicle routings are performed on pre-determined routes, which saves computation time.

We envision the use of our approach for training personnel in disaster preparedness and first response. By integrating our models in a computer-based simulation model, the planners and first responders can train within community-wide disaster scenarios. Instead of having large drills and tabletop exercises, they can evaluate their level of preparedness for different disaster scenarios while being trained. We already embedded SP and MIP models in a simulation and visualization environment developed for the Seattle area, called RimSim (Campbell et al., 2008). For disaster response, our MIP model given in Section 4 is embedded as an optimization module in RimSim and provides support for the transportation of materials from warehouses to hospitals, including the loading and routing of vehicles, so that medical logistics teams have a decision-support system while playing RimSim. RimSim also enables first responders to familiarize themselves with other roles in a response operation to improve situation awareness and distributed cognition.

7. Conclusions

We develop a stochastic programming approach for disaster preparedness to plan the storage and distribution of medical supplies to be used in emergencies. The proposed models provide interdisciplinary agencies with a means to prepare and respond to disasters by balancing the risk in an efficient way. According to the expected disasters with their magnitudes, our SP model determines an optimal policy of warehouse selections and inventory levels in the first stage and a collection of recourse decisions on transportation plans in the second stage for each disaster scenario. The aggregated transportation plans produced by the SP model are converted to a detailed optimal routing plan of vehicles with their loading amounts of medical supplies in an MIP model.

We demonstrated our approach on a case study for earthquake preparation in the Seattle area. However, our methodology is applicable to any other city with the necessary data provided by different stakeholders of disaster management.

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