EMERGENCY LOGISTICS FOR DISASTER MANAGEMENT UNDER SPATIO-TEMPORAL DEMAND CORRELATION: THE EARTHQUAKES CASE

RODRIGO A. GARRIDO*
Av. Ejercito 441, Santiago Centro
Santiago, Chile

IVAN AGUIRRE
Diagonal Las Torres 2300
Santiago, Chile

(Communicated by Gerhard-Wilhelm Weber)

Abstract. Emergency logistics is crucial to ameliorate the impact of large earthquakes on society. We present a modeling framework to assist decision makers in strategic and tactical planning for effective relief operations after an earthquake’s occurrence. The objective is to perform these operations quickly while keeping its total expenses under a budget. The modeling framework locates/allocates resources in potentially affected zones, and transportation capacity is dynamically deployed in those zones. Demand uncertainty is directly incorporated through an impulse stochastic process. The novelty of this approach is threefold. It incorporates temporo-spatial dependence and demands heterogeneity. It incorporates the availability of transportation capacity at different zones. It incorporates tight budget constraints that precludes the total satisfaction of demands. The resulting model is a large size stochastic mixed-integer programming model, which can be approximately solved through Sample Average Approximation. An example is provided and a thorough sensitivity analysis is performed. The numerical results suggest that the response times are highly sensitive to the availability of inventory at each period. In addition, all logistics parameters (except for inventory capacity) have approximately the same impact on the total response time. The elasticity for all these parameters indicate constant returns to scale.

1. Introduction. Logistics management is a complex task, even in the absence of anomalous conditions. It is so because it aims to satisfy demands in the best possible way considering different aspects such as time and budget constraints, unexpected demands, shortages, to mention a few elements. Emergency logistics finds an even more complicated environment to perform its duties. In fact, it must deal with deep uncertainty, poor communication between agents, deterioration in transportation networks, lack of knowledge about the magnitude of the encountered disasters, among many others that conform a set of extremely difficult constraints, conditioning the range of maneuvers available to decision makers. One particular case is
that of large earthquakes. These events are among the most unpredictable natural disasters in, at least, three dimensions: location, timing and magnitude. In spite of these technical difficulties to forecast them, it is necessary to carry out the best possible technical planning and execution of emergency plans, deploying trained personnel and basic survival supplies for rescue operations, as well as vehicles that allow the proper transportation of these elements at the right time to the right place. Earthquakes can devastate large areas in a matter of seconds, consequently, real-time decisions must be made to minimize the damage. Therefore, the success of any logistics effort after a large earthquake depends on the optimization of scarce resources to assist the affected population in the fastest possible way, within budgetary constraints. Hence the role of operations research tools to provide efficient solutions to the decision makers.

From the logistics perspective, the main difficulty after an earthquake occurrence lies in the uncertainty posed by the disaster. The earthquake triggers a sudden increase in the demand for specialized supplies and personnel (usually non-existent during normal times) reaching unexpected high levels, often forcing decision makers to improvise plans with lack of information and preparation [20], leading to great losses in terms of human lives and economic resources.

This article presents an emergency logistics modeling framework to attain two objectives: to deliver emergency supplies to the affected population in a timely manner, while at the same time, maintaining control of the expenditure in such a way that all the logistics costs are within a given budget.

The remainder of the article is organized as follows. Section 2 presents the literature review. Section 3 introduces the system to be analyzed, as well as the pertinent actors within the methodological framework. Section 4 presents the optimization model. Section 5 introduces a solution approach. A numerical analysis is presented in Section 6 along with a complete sensitivity analysis. Finally, Section 7 presents the conclusions.

2. Literature review. From the perspective of this research, there are two main areas of literature to review. On one side, any planning for emergency logistics involving earthquakes needs some degree of forecasting. In fact, either the location and/or magnitude of the earthquake are inputs to optimize the resources’ deployment. A significant number of articles deal with modeling the stochastic aspects of earthquake occurrence and magnitude. On the other hand, logistics design aspects of emergency/humanitarian operations play a key role in strategic and tactical plans to control the damage after an earthquake. This part of the literature is less developed than the first one. In the following two subsections we review the most relevant articles dealing with both issues.

2.1. The occurrence of an earthquake and its magnitude. Seismic hazard analysis (SHA) is the formal field for long-term predictions of the occurrences of seismic events. Although SHA can be approached from both the stochastic and deterministic perspectives, we will concentrate in the stochastic perspective, named probabilistic seismic hazard analysis (PSHA). Models based on PSHA are more comprehensive and they tend to forecast the events more accurately than its deterministic counterpart. In fact, they incorporate the inherent random nature of earthquakes’ magnitude, recurrence time, and other relevant features [19]. The first PSHA formulation was published in 1968 [11]. Later, [5] presented one of the most
complete illustrative compilations of the PSHA models. Most of the PSHA models perform the earthquakes’ forecasting as the probability of an event exceeding a given magnitude over a specified period of time. The assessment of these probabilities has relied on various stochastic formulations. For example, [19] lists various important parameters to characterize the concept of seismic hazard. Some of these parameters are the peak ground acceleration [11], response spectrum amplitudes [25, 6, 7], strong motion duration [30], soil liquefaction [40], and landslides [13], to mention the most widely studied. Due to its simplicity and relative ease of application, homogenous Poisson models have been the most popular choice in the literature [5]. However, they are limited in their representation of earthquakes’ driving mechanisms, mainly due to their strong assumptions of temporal and spatial independence and homogeneity. Those assumptions have proven to be a major limitation when characterizing large infrequent events. Most of the non-Poissonian models attempt to represent patterns of geophysical characteristics that would trigger the earthquakes’ occurrence mechanism. According to [5] those models emerge as the most promising tools. The time dimension, expressed by seismic gaps, seems to be highly relevant. These gaps are best represented through time dependent models. There is enough evidence showing that the spatio-temporal dependent models provide better hazard estimates than those of Poisson models. Nevertheless, these more sophisticated models are difficult to implement in practice and they require large datasets for parameter calibration. From the historical records it is possible to identify characteristics such as fault strike (direction of a line created by the intersection of a fault plane and a horizontal surface), fault rake (direction in which a hanging block moves during a rupture, with respect to the plane of the fault), slip (distance the hanging block moves relative to the foot block, in the direction given by the rake), fault dip (angle between the fault and a horizontal plane), friction conditions, etc. All of these conditions are spatially dependent. Examples of articles dealing with the various different conditions that an earthquake could exhibit can be found in [31, 32], [29]. There are other approaches that rely on the opinions of experts to draw conclusions about the seismic hazard. Those methods collect multiple expert opinions merged into econometric models to estimate the seismic hazard. Though the idea sounds intuitively right, [21] shows that those models are intrinsically defective and should not be used in engineering applications.

Summarizing, in order to capture the true aspects of an earthquake’s occurrence, any PSHA model should incorporate the heterogeneous spatial effects as well as a time dependent component. The model used in this article includes both aspects and it will be described in detail in Section 4.

2.2. Emergency logistics: The case of earthquakes. This area is less developed than that of seismic hazard analysis. Indeed, the interest in this field is relatively new and hence the amount of specialized literature is rather low and so is its level of sophistication when compared to the methodological advances in the geological aspects of earthquake occurrences. Nevertheless, there is a number of publications on emergency logistics related to natural disasters in general, i.e. not specifically oriented to earthquakes. According to [10] there are two types of disaster operations: before and after an event’s occurrence. Thus, short-notice evacuation, facility location, and inventory pre-positioning can be grouped as the main pre-disaster operations; on the other hand, relief distribution and casualties’ transportation can be grouped as post-disaster operations. The majority of the technical literature regarding earthquake emergencies is related to three topics: information
systems, search-and-rescue and evacuation. The topic of optimization of resources for humanitarian aid is even less developed than those two topics. In this topic [34] presents the first formal definition of of inventory pre-positioning (IPP) as: “The strategic positioning of inventory in the relief network in preparation for disasters, through the integration of facility location, inventory management and transportation decisions, while taking into account the key factors affecting it, to improve the response and efficiency of the relief network”. The following articles tackle (either directly or indirectly) the IPP problem from an OR perspective. [14] address the topic of search-and-rescue from the perspective of optimal allocation of resources to operational areas through a dynamic combinatorial optimization model solved through Simulated Annealing and Tabu Search. The model however, does not consider the supply of emergency products to be delivered to the rescued people (or rescue teams) therefore there is no inventory optimization or distribution strategies to that end. [23] proposed an agent based evacuation model in which pedestrians and car drivers are agents who decide where to go and how to reach their evacuation route. This model does not optimize the deployment of personnel/supplies to the affected areas. [39] developed an information system aimed to promote earthquakes’ mitigation practices for residents of potentially affected areas. Their information system was able to compute hazard values at individual level.

[38] put forward a methodology to address the problem of logistics coordination to support dynamic relief demands. The objective function combined both the degree of urgency and the (more traditional) transportation costs. Later, [37] refined the relief demands forecasting in large-scale natural disasters, through a dynamic relief-demand management model. [8] also studied the problem of demand uncertainty in humanitarian relief supply chains, as a dynamic traffic assignment problem. They studied the problem of generating evacuation plans in such a way that their performance is robust to uncertainty in outgoing demand. [33] studied logistics planning under incomplete and fuzzy information. They proposed a simulation model to deal with uncertainties in predicting post-seismic transportation network and delayed information. The main objective was to analyze the behavior of disrupted supply chains under post-disaster conditions. [45] studied the case of optimal location of distribution centers with the explicit incorporation of social cost components. Their article was mostly concerned with the algorithm to solve the model and the geometry of the solutions. Also [24] studied the case of disruption of network services, focusing on a prioritized restoration of the damaged infrastructure within budgetary constraints. These authors followed a multi-objective optimization approach in which the model needs to balance cost minimization and system flow maximization. [27] studied the transportation network disruption in disaster relief operations with capacity constraints, incorporating two novel features: counterflow traffic on the arcs and the obstruction caused by the relief trucks, through a dynamic arc routing model. [43] studied the evacuation through a surface network when the demand is uncertain. The authors proposed a robust optimization scheme leading to a linear programming model. The authors showed that their robust solution dominates a deterministic solution. [42] pointed out the location of distribution centers and vehicle routing as two of the most challenging problems in emergency logistics. They built a non-linear integer location-routing model for relief operations considering multiple objectives: travel time, the total cost, and reliability with split deliveries. The model was applied to the Great Sichuan Earthquake in China.
[15] performed a compared literature review in the field of disaster operations management. The first review was done in 2006 by [4], which sets the base for comparison with the newer developments presented in [15]. Surprisingly, those authors found no drastic changes or developments in the studied field. Among the optimization-based mathematical models for emergency/humanitarian logistics, there are only a few that deal with uncertainty. Those models tackle the uncertainty problem in two-stage processes [41]. Good examples of the latter are [3] and [1], who divide a difficult problem into two phases to find an approximate solution.

Some studies have focused on a specific aspect of the relief, instead of a comprehensive approach. For example, [12] present an extension of the newsvendor model to analyze the case of a single agency that stocks inventory in preparation for a disaster. They also extended their model to the case of two agencies, assuming Nash equilibrium conditions between cooperative agencies. Their model however, assumes that there is always enough transportation capacity to deliver the emergency supplies, and it concentrates in the inventory decisions under equilibrium conditions. Also [36] focused on a specific aspect of the emergency logistics, which is the spatial impact of a disaster on transportation network links and its adverse affects on the accessibility to demand points. Those authors later extended the model [44] to increase the resilience of a transportation network through optimal investment in the links strength. [35] performed a Delphi study to identify the most relevant factors taken into consideration by decision makers facing humanitarian emergencies. The following factors rank at the top five of their list: speed of emergency response, availability of infrastructure, availability of business support services, cost of operating facilities, and the availability of labor. Most of those factors are related to facility location problems. Within this category, [9] present a complete survey of the main problems in the emergency humanitarian logistics literature. They found four clusters: deterministic facility location problems, dynamic facility location problems, stochastic facility location problems, and robust facility location problems. Two aspects of their findings are relevant to this article. First, most of the analytic models take either a dynamic or a stochastic approach, rather than both simultaneously. Second, the stochastic cluster has only a handful of examples in the literature.

Aiming at the objectives defined above and the gaps found in the pertinent literature, the emergency logistics approach that we propose is unique in the following aspects:

i) Our PSHA incorporates temporal and spatial dependence and heterogeneity simultaneously. This fact avoids the major limitations of Poissonian approaches when characterizing large infrequent events. The occurrence of a large earthquake is simulated using Monte Carlo experiments with a given probability. In addition to that probability, our approach incorporates a conditional probability for the magnitude of the event.

ii) Our methodology incorporates not only the availability of emergency products but also the availability of transportation capacity at different zones, which can be dynamically assigned to each zone.

iii) Our methodology also considers tight budget constraints that, as in real cases, preclude the total satisfaction of all the demands. Instead, the model finds the optimal resource allocation scheme that guarantees a percentage of demand satisfaction (level of service) across the affected zones.
3. Emergency logistics systems. Natural disasters lead to extended damage and the onset of extremely high demands for certain supplies. These aspects must be addressed as quickly as possible. The latter needs the coordination among relief suppliers and transportation providers to assist victims in a timely manner. Thus, prepositioning models are useful tools to assist authorities in the optimal location/allocation of resources such as supplies, human resources or transportation capacity. The optimal location/allocation of resources includes the minimization of response time, thus mitigating the damaging effects of the disaster [2]. The main agents involved in emergency logistics are described below.

3.1. Suppliers. In this category, we include all agents that offer products that victims of an earthquake typically need. Suppliers own or lease warehouses where their products are stored, for further distribution. These facilities are strategically located to serve specific geographical areas. The prices of these products can vary among different periods and providers, but for the sake of simplicity, we assumed that the prices are constant throughout the modeling periods and that it is possible to locate at least one facility at each potentially affected area.

3.2. Transportation providers. Agents in this category own vehicles that could be used to distribute supplies to areas with needs. Each provider may have vehicles at different geographical sites, similar to the case of the suppliers. Service rates are often based on the weight and volume of shipments, as well as the travelled distance for delivery. As in the case of the suppliers, these rates also can vary in time and among carriers. It is worth noting that there are limitations in transportation modes; for example, certain products require temperature-controlled vehicles while others could be delivered in standard vehicles; hence, supplies cannot be transported by any vehicle but only by those technically apt.

3.3. Zones. These are sites where demand emerges, i.e., the geographical points affected by an earthquake, where the emergency supplies are needed. The demand in a geographical area equals the aggregation of demands from all the affected individuals within the boundaries of that area.

3.4. Problem statement. The situation described in the previous sections is rather difficult to address. No single undertaken action could solve the problem of distributing resources in space and time to guarantee a total demand satisfaction in a timely manner. Once an earthquake strikes a region, the authorities need a quick and coordinated palliative reaction. This reaction must involve all the above described agents to satisfy at least partially the emergent demands. Most of these demands emerge only as a result of the earthquake and consequently, the standard market response is incapable of satisfying these new demands. Then, the pertinent question is What actions could be taken, before and after an earthquake, to minimize its consequences? One such action is the proper anticipation of spatial demand for emergency supplies. This anticipation leads to the pre-positioning of inventory at certain sites to reduce the access time and logistical cost of satisfying the urgent needs [20]. Another action is the allocation of transportation capacity to potentially affected regions. Human resources could also be planned before the event. After the event, the actions should focus on the prompt delivery of emergency supplies and personnel, given the previously allocated resources. With these actions in mind, we developed a modeling framework that aims to optimize the location/allocation and
distribution of the various resources involved in emergency logistics. The modeling framework builds upon the previous works by [16] and [17] who applied chance constrained optimization for a stochastic minimum cost problem; in our case however, the minimization of response times seems to be a more adequate goal, while a budget constraint allows the control of the operational expenses. Such a modeling framework is presented next.

4. Modeling framework. The modeling structure developed in this article differs from previous studies in, at least, three aspects. First, the stochastic demand takes space and time into account, assuming non-zero correlations in both dimensions. Second, the cost matrix considers not only direct inventory and distribution costs but also the fleet relocation costs necessary to perform each shipment (it includes the possibility of moving empty vehicles from different locations). Third, given the sudden and unexpected characteristics of the demand, the model allows the fill-rate be lower than 100%, attaining the best possible level of service for the available budget.

This Section is divided into two parts. The first one describes the earthquakes simulation and its corresponding demand generation process. The second section presents the optimization model, taken the demand as a given parameter.

4.1. Earthquake occurrence and demand simulation. Some of the most comprehensive models described in the reviewed literature incorporate the fact that earthquakes are the result of multiple causes —technically called triggers. Each trigger can be associated with a probability. Thus, an earthquake is the outcome of the interaction of a compound process (representing the triggers) and a set of particular conditions that make the result more or less severe (e.g. infrastructure and housing conditions, type of structural design, etc.).

Once a significantly large earthquake occurs, there is an immediate generation of demand for certain emergency supplies (e.g. fresh water, vaccines, etc.). Then, the magnitude and composition of the demand will change randomly according to both the initial conditions and the severity and scope of the emergency. While some of the initial conditions can be accurately known (such as inventory at hand, and operational characteristics of potentially affected zones), other conditions cannot be predicted with acceptable degrees of accuracy (e.g. severity and frequency of the aftershocks). Therefore, it is convenient to use a stochastic approach to estimate the effect of demand uncertainty on the delivery of emergency supplies. There are two different stochastic processes acting simultaneously: the occurrence and the severity of the shock. It seems reasonable then to assume that the demand for emergency supplies is proportional to the severity of the shock. This assumption implies that the demand function is a chained two-dimensional process: on one side there is a probability that a shock occurs at any given time, and on the other hand, there is a conditional probability of having a certain magnitude of demand given that the shock has occurred. Accordingly, the demand process can be expressed as follows:

**Definitions.** $D_{tp}^i$: Stochastic variable representing the demand for (emergency supply) product $p$, at zone $i$, during period $t$

$d_{tp}^i$: A realization of $D_{tp}^i$.

$p_t^i$: Probability that a sufficiently large earthquake (disruptive) occurs at zone $i$ during the time interval $t$.

$\rho_{p_{ij}}^{t_0,t_e}$: Spatiotemporal correlation for earthquake occurrences between two
different zones $i$ and $j$, with a seismic gap of magnitude $(t_b - t_a)$, for any time periods $(t_b > t_a)$.

$\rho_{t_a, t_b}^{i,j}$: Spatiotemporal correlation for the emergency demands between two different zones $i$ and $j$, with a seismic gap of magnitude $(t_b - t_a)$, for any time periods $(t_b > t_a)$.

$$D_{i}^{t_p} = \begin{cases} \ d_{i}^{t_p} \text{ with probability } p_{i}^{t} \\ 0 \text{ with probability } 1 - p_{i}^{t} \end{cases}$$

We used a series of Monte Carlo experiments to generate the demands at each time step, location, and magnitude. The magnitude of the earthquakes were simulated following an iid lognormal distribution, while the occurrence of earthquakes in time and space were not independent, but correlated using random values for $\rho_{t_a, t_b}^{i,j}$ and $\rho_{t_b, t_a}^{i,j}$. The latter simulates the findings in the literature (i.e., certain zones are more likely to exhibit triggers than others, and events also depend on the time elapsed after the triggers occurrence). The number of time periods and spatial units vary according to the case to be studied (see Section 6).

### 4.2. Optimization model.

The modeling framework needs the following parameters and variables.

**Parameters**

- $u_c$: Capacity for class $c$ vehicles.
- $w_{pc}$: Compatibility matrix; its elements $(p, c)$ take the value 1 if product $p$ can be transported on a class $c$ vehicle; and it takes the value 0 otherwise.
- $\tau_{ij}$: Travel time between zones $i$ and $j$.
- $G$: A positive large number.
- $B$: Budget available for the planning horizon.
- $\Phi$: Set of all the potentially affected zones.
- $\Pi$: Set of all the potentially demanded products.
- $\Psi$: Set of periods.
- $\Omega$: Set of vehicle classes.
- $D_{i}^{t_p}$: Demand for product $p$, in location $i$, during period $t$.
- $V_{i}^{t_c}$: Number of class $c$ vehicles, available in zone $i$, at the beginning of period $t$.
- $L_{i}^{p}$: Inventory capacity at zone $j$, for product $p$.
- $Cv_{i}^{t_p}$: Direct cost of transporting one unit of product $p$, to the zone $k$, originated from a supplier in zone $j$, transported on a class $c$ vehicle available in zone $i$, during period $t$.
- $Cl_{i}^{t_c}$: Cost of relocating a class $c$ vehicle, sent from zone $i$ to zone $j$, during period $t$.
- $Ch_{i}^{t_p}$: Inventory (holding) cost for product $p$, stocked in a depot located in zone $j$, during period $t$.

**Decision Variables**

- $x_{i}^{t_p}$: Flow of product $p$, sent to location $k$, originated from a supplier in location $j$, transported on a class $c$ vehicle available at location $i$, during period $t$.
- $y_{i}^{t_c}$: Flow of class $c$ vehicles, relocated from zone $i$ to zone $j$, during period $t$.
- $I_{j}^{t_p}$: Inventory of product $p$, kept in depot located in $j$, at the beginning of period $t$.
- $WP_{i}^{t_p}$: Takes value 1 if product $p$ is delivered to zone $k$, from a supplier located in $j$, transported on a vehicle available at $i$, during period $t$; and 0 otherwise.
\(WC_{ij}^{tc}\): Takes value 1 if a class \(c\) vehicle is relocated from zone \(i\) to \(j\), during period \(t\); and 0 otherwise.

Given the definitions stated above, the following mixed integer stochastic programming model is aimed to guide the decision makers in the strategic and tactical aspects of emergency assistance to the affected zones:

\[
\min \left( \sum_{i \in \Phi} \sum_{p \in \Pi} \sum_{k \in \Phi} \sum_{j \in \Phi} \sum_{c \in \Phi} \tau_{jk} WP_{ijk}^{tp} + \sum_{i \in \Phi} \sum_{p \in \Pi} \sum_{j \in \Phi} \sum_{c \in \Phi} \tau_{ij} WC_{ij}^{tc} \right)
\]

\(P \left\{ \sum_{c \in \Omega} \sum_{i \in \Phi} \sum_{j \in \Phi} x_{ij}^{tpc} \geq D_{ik}^{tp} \; \forall k \in \Phi, \; t \in \Psi, \; p \in \Pi \right\} \geq \alpha \) \hspace{1cm} (3)

\[
\sum_{p \in \Pi} \sum_{j \in \Phi} \sum_{k \in \Phi} w_{pc} x_{ij}^{tpc} \leq \sum_{c \in \Phi} u_{c} y_{ij}^{tc} \; \forall c \in \Omega, \; i \in \Phi, \; t \in \Psi \]

\(\forall i \in \Phi, \; t \in \Psi, \; c \in \Omega \)

\[
\sum_{c \in \Omega} \sum_{i \in \Phi} \sum_{j \in \Phi} x_{ij}^{tpc} \leq I_{jp} \; \forall j \in \Phi, \; p \in \Pi, \; t \in \Psi \]

\(I_{jp} \leq L_{j}^{p} \; \forall j \in \Phi, \; p \in \Pi, \; t \in \Psi \) \hspace{1cm} (7)

\[
\sum_{i \in \Phi} \sum_{j \in \Phi} \left( \sum_{p \in \Pi} \sum_{k \in \Phi} \sum_{c \in \Phi} C_{ijk} x_{ij}^{tpc} + \sum_{c \in \Omega} \sum_{i \in \Phi} \sum_{c \in \Phi} Cl_{ij}^{tc} y_{ij}^{tc} + \sum_{p \in \Pi} Ch_{ij}^{tp} I_{jp}^{tp} \right) \leq B \) \hspace{1cm} (8)

\(x_{ij}^{tp} \leq WP_{ijk}^{tp} G \; \forall i \in \Phi, \; j \in \Phi, \; k \in \Phi, \; p \in \Pi, \; t \in \Psi \) \hspace{1cm} (9)

\(y_{ij}^{tc} \leq WC_{ij}^{tc} G \; \forall i \in \Phi, \; j \in \Phi, \; c \in \Omega, \; t \in \Psi \) \hspace{1cm} (10)

\(x_{ij}^{tp}, I_{jp}^{tp} \in \mathbb{R}^{+} \; \forall i \in \Phi, \; j \in \Phi, \; k \in \Phi, \; p \in \Pi, \; t \in \Psi \) \hspace{1cm} (11)

\(y_{ij}^{tc} \in \mathbb{Z}^{+} \; \forall i \in \Phi, \; j \in \Phi, \; c \in \Omega, \; t \in \Psi \) \hspace{1cm} (12)

\(WC_{ij}^{tc}, WP_{ijk}^{tp} \in \{0, 1\} \) \hspace{1cm} (13)

The objective function (2) has two terms: the travel time to deliver aid from the suppliers to the affected areas, and the repositioning time, i.e. the time needed to relocate vehicles (of a given type) at the suppliers locations. The constraints set (3) assures that demand for emergency supplies is satisfied with a probability \(\alpha\), i.e., not all the demands will necessarily be satisfied but at least \(\alpha \times 100\%\) of the requests will be fulfilled. The constraints set (4) restricts the fleet capacity; given a vehicle type \(c\), a location \(i\) and a period \(t\), the left-hand side shows all the flow of products in type-\(c\) vehicles, while the right-hand side shows the total capacity of those vehicles available at the origin of the trip. The constraints set (5) controls the stock of vehicles at each zone and time period. The constraints set (6) precludes that the amount of transported products exceeds the available inventory at a given zone. The constraints set (7) controls that the initial stock level does not exceed the inventory capacity. Constraint (8) ensures that the whole emergency operation does not exceed the available budget. The constraints sets (9) and (10) establish consistency between binary and flow variables. Finally, the constraints sets (11) and (12) impose non negativity and integrality, while the constraint set (13) correspond to the binary condition.

The model (2) to (13) is rather difficult to solve, not only for the integrality aspects and size of any real instance, but particularly because of the expression (3),
which is a joint probability function of size $|\Phi| \times |\Pi| \times |\Psi|$. What this probability constraints is the minimum overall demand to be satisfied (not each $(k, t, p)$ component individually). In fact, many combinations of individual demand satisfaction levels could add up to meet the overall $\alpha$ desired level. That particular condition makes this problem intractable with standard OR methods.

One of the methods that has proved to be successful is the Sample Average Approximation that will be presented in the next section.

5. Solution approach. In this section, a solution scheme called Sample Average Approximation (SAA) is briefly introduced and implemented (following [28]). Instances of stochastic programming models with large number of stochastic constraints are computationally intractable. This is the case with the stochastic set represented in expression (3). Indeed, the values of each probability in expression (3) are difficult to compute, because they require to evaluate multi-dimensional integrals (one for each product, time and affected zone); even checking feasibility of a solution is difficult to perform [22]. In addition, the convexity of the feasibility region is not guaranteed. These features preclude the direct search for an optimal solution of the original problem. Hence a heuristic approach should be applied to find an approximation to the optimal solution. The SAA approach attempts to replace the probabilities in expression (3) by deterministic values given by a frequency (estimators of the true probability) and then, solving a series of deterministic optimization models in which the frequency is a proxy for the probability of satisfying the demands with the given fill-rate. Thus, a series of (simpler) deterministic models must be solved instead. The set of approximated solutions found by SAA allow us to identify two relevant limits for the objective function: a lower and an upper bound. The lower bound will typically be an infeasible solution to a relaxed problem (not necessarily restricted to fulfill the given level of service) that serves as a threshold below which no solution can be found for the original problem. On the other hand, the upper bound is a feasible solution, whose value is, typically, not low enough to be the minimum for the objective function. Thus, the optimal value for the original problem, lies somewhere in between these two thresholds. The gap between these two bounds gives a measures of the closeness of the best feasible solution to the optimal solution. Nevertheless, any upper bound can be used to assist DM in the process of planning for earthquake damage control. Indeed, the upper bound is an approximate solution that sheds light on the recommended depot locations, supplies prepositioning at different locations, fleet size required to deliver the supplies and such. Note however, that the SAA heuristic cannot guarantee that the cost/time of that feasible solution is the minimum among all feasible solutions.

The vector of stochastic demands is generated through Monte Carlo experiment, in which the value of the simulated demands are drawn from a random sample with the spatio-temporal correlations described in section 4.1.

Thus, if the probability in expression (3) were replaced by its estimator, i.e. a frequency computed out of a sample, we could formulate a new problem as an approximation to the original one. The new model would have two differences with respect to the original model in expressions (2) to (13). First, instead of expression (3), which represents the stochastic demand constraints, we introduced a sampling method in which the original constraints are replaced by the frequency of demand fulfilment, estimated by solving many instances of the modified problem, each time with a different set of demands computed through a Monte Carlo experiment.
Second, the number of times that demands are not satisfied must be restricted to the desired level of service ($\alpha$ in expression (3)). Let $z^{ntp}_k$ be binary variables that count the number of times that a demand is not satisfied in the $n$-th draw, i.e. not enough supplies are delivered to fulfil $D^{ntp}_k$ in expression (3). With this new definition we can modify the original model in expressions (2) to (13), to find the solution to a similar problem but without stochastic components. If we solved this approximation for various samples (independently generated) the optimal solution of the approximated problem will be approximations to the original optimal solution. Therefore, the constraints set (3) is replaced by the following three sets of constraints:

$$\sum_{i \in \Phi} \sum_{j \in \Phi} X^{ntpc}_{ijk} + z^{ntp}_k \times D^{ntp}_k \geq D^{ntp}_k \quad \forall k \in \Phi, p \in \Pi, t \in \Psi, n = 1, \ldots, N$$ \hspace{1cm} (14)

$$\sum_{n=1}^{N} \sum_{t \in \Psi} \sum_{p \in \Pi} \sum_{k \in \Phi} z^{ntp}_k \leq N \times (1 - \gamma)$$ \hspace{1cm} (15)

$$z^{tnp}_{kp} \in \{0, 1\} \quad \forall k \in \Phi, p \in \Pi, t \in \Psi, n = 1, \ldots, N$$ \hspace{1cm} (16)

where, the upper index $n$ is the sample number; $N$ is the sample size, and $\gamma$ is the desired level of service to solve the approximated problem. Constraints set (15), controls the number of times that the demand satisfaction is not fulfilled (it cannot exceed $1 - \gamma$). Note that $z^{ntp}_k$ in expression (14) allows to disable the demand satisfaction to a desired degree. In fact, by selecting the proper $\{0, 1\}$ combination of $z^{ntp}_k$, many level of services can be achieved. For instance, for a 90% level of service, the model allows $z^{ntp}_k$ to take any combination of 1’s as long as the total number of 1’s does not exceed 10% of the sample. Note also that $\gamma$ is not necessarily equal to $\alpha$ because, as we will see in the next section, sometimes it is convenient to have a different value for $\gamma$ in the search for solution bounds.

Each one of these modified models increases the problem size even more; therefore, the recommended solution procedure is to find lower and upper bounds to establish the space within which the optimal solution lies.

6. Numerical example.

6.1. Description. In this section a numerical example is presented, applying the above described methodology to obtain both the lower and upper solution bounds. Before going into the details of the numerical example, it is convenient to summarize the solution approach presented in Section 5. Indeed, lets assume that we have a simplified version of our main problem, i.e. for a single period, a single supply must be distributed by a single supplier, on homogeneous vehicles, to four affected zones. In this case the expressions (14) to (16) would look as follows:

$$X^{n}_{11} + z^{n}_{1} \times D^{n}_{1} \geq D^{n}_{1}$$ \hspace{1cm} (17)

$$X^{n}_{12} + z^{n}_{2} \times D^{n}_{2} \geq D^{n}_{2}$$ \hspace{1cm} (18)

$$X^{n}_{13} + z^{n}_{3} \times D^{n}_{3} \geq D^{n}_{3}$$ \hspace{1cm} (19)

$$X^{n}_{14} + z^{n}_{4} \times D^{n}_{4} \geq D^{n}_{4}$$ \hspace{1cm} (20)

$$\sum_{k=1}^{4} z^{n}_{k} \leq 3$$ \hspace{1cm} (21)

$$z^{n}_{k} \in \{0, 1\} \quad \forall k = 1, \ldots, 4, n = 1, \ldots, N$$ \hspace{1cm} (22)
Of course, if all the solutions for a given sample satisfy (17) to (22) that is no guarantee that all possible demand values in expression (3) will be satisfied with the desired level of service. However, a sufficiently large value of \(N\) and also running the approximation model for a sufficiently large number of samples (say \(M\) samples) should give us a high likelihood that the found solutions lay within the \(\alpha\) level of service. In fact, choosing a tightened value for \(\alpha\) would prevent the approximated solution to violate the original level of service; hence the need for the parameter \(\gamma\) (see [26] for the demonstration that SAA converges to the actual solution).

The numerical example to be presented is formed by a base-case instance with six zones, four periods, two products and two types of vehicle. As explained in section 4.1, the demand is generated through a Monte Carlo experiment that takes the spatial and temporal correlations into consideration. These correlations (\(\rho_{p,t}^{i,j}\) and \(\rho_{d,t}^{i,j}\)) were randomly chosen from the real interval \([0,1]\). To avoid the possibility of negative values of \(d_{t,i}^{p}\), the magnitude of demands at each zone were drawn from a lognormal distribution with (arbitrary) mean = 100 and standard deviation = 20. In each period, the probability of an earthquake occurrence was taken as 0.1, and the values of space and time correlations were chosen randomly. For this base-case example, an approximation of the optimal solution was found by computing the lower and upper bounds as described in the previous section, using a Mac Mini equipped with Mac OS Mojave version 10.14.1, an Intel Core i5 processor with 2.8 GHz speed, and 8 GB of internal memory.

6.2. Lower bound. [28] (and also [18]) describe the details on how to obtain convenient values for \(M\) (number of samples) as well as \(N\) (each sample size) to attain the desired level of fill-rate in expression (3). Applying that method for this instance we found: \(M = 172\) samples, each with \(N = 20\) (sample size), for the values: \(\alpha = 0.9\) and \(\gamma = \alpha/2\), (this selection of \(\gamma\) has been reported to exhibit efficient algorithmic behavior [26]).

Using CPLEX 12, the modified optimization problem (presented in Section 5) was solved generating demands with a Monte Carlo simulation routine using the parameters given above. The optimization model was ran for all the instances (i.e. for the \(M\) samples and \(N\) realizations) on the above described computer, with CPU time ranging from 23 to 39 seconds per ran.

The obtained solutions (which are an approximation to the true model) gave a lower bound (objective function’s value) of 2,900.

6.3. Upper bound. To obtain the upper bound, we followed the method described in [18]. In this case, the solutions must be feasible. Therefore, after finding the solutions for the modified problem, those solutions must be tested to guarantee that they satisfy the corresponding actual constraints, in expression (3). The parameters for this base-case instance were the following: \(N = 30\), \(\gamma = \alpha/2\) and the testing sample size was 400. Hence, 400 randomly generated demands were tested for feasibility. The CPU time varied from 31 to 59 seconds per ran.

The found solution was feasible in 90% of the 400 generated demands (in accordance with the level of confidence set by \(\alpha = 0.9\)). Thus, the best objective function’s value found by this heuristic (upper bound) was 3,900.

The gap between both bounds is 34%. This gap may appear to be large in comparison to other published results [22]. However, the type of problem addressed in this case is rather different from those published in the literature. Indeed, earthquakes tend to be low probability-high consequence events, which means that the
stochastic parameters exhibit a high variability when compared to other problems. In this case the demand’s variability is significantly larger than that of the reported instances, due to the shape of the demand curve (essentially a spike in a given period and zero elsewhere). In fact, for the case of floods studied by [18] with a similar spike-shaped demand, the best gap found was 31%, which is quite close to our result.

The SAA results, allow us to conclude with high level of confidence, that the upper bound found by this approach is a feasible solution whose value is at most 34% far from the unknown optimal solution. This information may be of great value to the decision makers (DM), even though it is only an approximation, but it serves as a guide to set up emergency preparedness actions. Indeed, the DM would have information about prepositioning, vehicles availability, time to reach the affected population and the impact of an increase (or decrease) in the available budget on the emergency demands satisfaction rate.

6.4. Sensitivity analysis. The above sections assumed various parameters to estimate the best feasible solution in a practical scenario. Those parameters would be estimated and used by the decision makers (DM) before the earthquake occurs, and hence are subjected to change when the actual disaster occurs. Then, DM should have an estimation of how sensitive their logistics system is to changes in the relevant parameters. To test this sensitivity, this section reports on the objective function’s response to perturbations on the original parameter’s values, i.e. how sensitive the objective function is to variations around the values selected for the numerical example. Special attention should be put if the objective function would present large variations as a result of minor variations in the original parameters. Indeed, the effect of all the parameters is not homogeneous and then special efforts should be dedicated to the econometrics for estimating the most relevant parameters with high accuracy (whenever possible in practice).

The parameters tested in the sensitivity analysis are the following: Number of Periods, Number of Products, Number of Zones, Inventory Capacity and Level of Service. Many parameters were tested, but in this Section we present only those that had the most significant impact on the objective function values and are also meaningful to DM in practice. As a stochastic approach, the SAA methods yield different solutions for each realization. Consequently, the values reported in this Section are the average of the tested samples as well as its standard deviation as a proxy for the solution stability.

6.4.1. Results. The reported values correspond to the average and standard deviation for 100 samples each one with 20 realizations. Table 1 shows the different scenarios tested in the sensitivity analysis as well as the base case parameters.

| Parameters                      | Base | Scen. 1 | Scen. 2 | Scen. 3 | Scen. 4 |
|--------------------------------|------|---------|---------|---------|---------|
| Number of Periods               | 4    | 2       | 3       | 5       | 6       |
| Number of Products              | 2    | 1       | 3       | 4       | 5       |
| Number of Zones                 | 6    | 2       | 4       | 8       | 10      |
| Inventory capacity per period (units) | 100  | 90      | 95      | 105     | 110     |

Table 1. Sensitivity scenarios and parameters’ variations

The main results have been summarized in Table 2, which shows the percentage of variation of the objective function, i.e., the average response times, when different parameters are varied in each scenario (described in Table 1). Thus, each
value presented in Table 2 represents how sensitive the response time is to the corresponding changes in a specific scenario/parameter. For example, scenario 2 increases the Number of Products from 2 to 3, generating a 52% increase in the objective function’s average value.

Table 3 shows the Coefficient of Variation (i.e. ratio between standard deviation and sample average) for the objective function (travel and repositioning total time) for each scenario. It can be observed that the variation is rather low. The latter is an indication of the robustness of the solutions, i.e. the measure of impact of the different parameters on the objective function is stable throughout the various realizations.

Table 4 presents the elasticity values of a single change for each scenario. It can be seen that the Number of Zones (i.e. size of the network) the Number of Periods and the Number of Products have a similar elasticity, a little higher than unity (between 1.03 and 1.07), this means that an increase in the size (and complexity) of the problem represents an increase in the response time in a higher proportion. On the other hand, the Inventory Capacity per Period showed a strong negative impact on the response time; the elasticity of the Inventory Capacity parameter presented a strong asymmetric variation with the sign of the change. Indeed, a decrease of 10% in the parameter had an elasticity of -0.87, while an increase of 10% had an elasticity of -1.85. The latter is due to the substitution effect between Inventory Capacity and transportation.
Therefore, this numerical example was repeated for probabilities of 2% and 1% and the solutions found by the model were compared to the base case (10%). A value of a higher occurrence probability (20%) was also tested. These results are summarized in Table 5, which shows two interesting findings. First, there is a significant reduction in the response time, though not as high as the probability reduction. In fact, when the probability of occurrence was reduced 5 times (from the base case), both bounds had a decrease of approximately by 75%; when the probability of occurrence was reduced from 2% to 1% both bounds were decreased by approximately 29%; on the contrary, when the probability was increased up to 20% the gap was reduced by 14%. Secondly, the gap increases as the probability of occurrence decreases. The latter is due mainly to the fact that the magnitude of each bound decreases jointly with the probability of earthquake occurrence, but at a slower pace than their difference, and hence the ratio between these values increases. This is another example of the effect of a sharp demand curve represented in the expression (4).

| Total Access Time | Earthquake Pr. = 20% | Earthquake Pr. = 10% | Earthquake Pr. = 2% | Earthquake Pr. = 1% |
|-------------------|----------------------|----------------------|----------------------|----------------------|
| Lower Bound       | 500                  | 700                  | 2,900                | 4,000                |
| Upper Bound       | 1,000                | 1,200                | 3,900                | 4,800                |
| Relative Gap      | 100%                 | 71%                  | 34%                  | 20%                  |
| Absolute Gap      | 500                  | 700                  | 1000                 | 800                  |

Table 5. Variation of the solution under different probabilities of earthquake’s occurrence.

6.4.2. Cost sensitivity analysis. The sensibility analysis presented in the previous section kept the cost parameters unchanged. A change in transportation costs does not affect the problem solution as long as the total costs are within the available budget. Therefore, it is interesting to study what happens when the budget parameter \( B \) changes. Indeed, from a public policy perspective, a valuable input would be to assess the relationship between the level of service (parameters \( \gamma \) or \( \alpha \)) and the available budget (parameter \( B \)). To perform this analysis we prepared a set of \( M \) samples of size \( N \), with different values for \( \alpha \). For each of these values we found the minimum value of \( B \) which allows a feasible solution for at least 95% of the \( M \) samples. The results are summarized in Figure(1).

As Figure(1) shows, decreasing the level of service (\( \gamma \)) from 10% to 5% would increase the need for budget by 5,000 units, and when it decreases from 5% to 2.5%, the needed budget would increase again by 5,000 cost units. The latter shows that improving the level of service becomes increasingly more expensive when approaching the 100% coverage. The values depicted in Figure(1) provide the DM with an estimate of how “expensive” would be to reach a certain percentage of demand satisfaction from the affected population.

6.4.3. Relevant information and decision making. Regardless of the particular scope of any numerical example, certain aspects of the found results deserve careful attention, as they may be helpful in the emergency planning of an earthquake.

One of the first results that emerge from the numerical examples is that the response times are highly sensitive to the availability of inventory at each period. The latter occurs under different parameter’s values and scenarios. The explanation for this behaviour is that for a given level of service, the model will attempt to
reach the fill-rate first with inventory at hand (to avoid excessive transportation) but when the inventory capacity is too low, it is imperative to satisfy emergency demands from locations farther away, increasing travel times and costs. Therefore, a first heads-up for DM is that time and costs can be reduced as long as the stock availability allows to reach the service goal from local or nearby locations. But, when the stock is limited, then the transportation times and costs take over. The values shown in the sensitivity analysis, though particular in scope, give a sense of frame reference for the non-linear behaviour of travel times as a response to low inventory levels. Another piece of information that could be helpful for DM is the fact that all logistics parameters (except for Inventory Capacity) have approximately the same impact on the total response time. Indeed, the elasticities for all these parameters indicate constant returns to scale. The practical implication of the latter is that changes in response times will be homogeneous under any change in the size of the instances in practice. Also, the effect of (moderate) changes to the initial logistics conditions will be linear.

7. **Final remarks.** In this article, a stochastic mixed integer programming model was developed with the aim of reducing response time for assisting victims of an earthquake. The model represents the various decisions made before and after the earthquake’s occurrence. The modeling framework considers inventory capacity, vehicles’ availability as well as expected demands for different emergency supplies. A sample-average approximation scheme (SAA) was implemented to find a solution to the problem. This type of problems exhibit the characteristic of low-probability high-consequence, which translates into an impulse demand curve, very difficult to incorporate into standard optimization techniques.

The modeled example (base case) considered six zones, two types of products and the vehicles needed for their transport, four periods and an inventory capacity
of one hundred units per zone. A sensitivity analysis was performed on the different parameters that affect the objective function. The results pointed out some critical parameters in terms of their impact on the emergency response times. These critical parameters were the storage capacity and budget size. These outcomes arise from the fact that increasing the local inventories allows the victims to satisfy their demands from local supply instead of waiting for external supplies to arrive; simultaneously, the budget size restricts the feasibility to execute such a preventive measure. Decision makers must consider that the low predictability of earthquakes makes difficult to implement such types of preventive measures at national level, especially because multiple products are in need during an earthquake, all with different expiration dates or useful life times, which increases the budget requirements to execute those measures. Nonetheless, a lower-scale plan could be incorporated in at-risk areas, by keeping a stock of easily stored high-necessity relief supplies. A possible future study could use this methodology with a more realistic scenario for Chile, i.e., with actual data collected from the involved agencies.

REFERENCES

[1] M. Ahmadi, A. Seifi and B. Toootooni, A humanitarian logistics model for disaster relief operation considering network failure and standard relief time: A case study on san francisco district, Transportation Research Part E: Logistics and Transportation Review, 75 (2015), 145–163.
[2] A. R. Akkihal, Inventory Pre-positioning for Humanitarian operations, Master’s thesis, Massachusetts Institute of Technology, USA, 2006.
[3] D. Alem, A. Clark and A. Moreno, Stochastic network models for logistics planning in disaster relief, European Journal of Operational Research, 255 (2016), 187–206.
[4] N. Altay and W. G. Green III, Or/ms research in disaster operations management, European Journal of Operational Research, 175 (2006), 475–493.
[5] T. Anagnos and A. Kiremidjian, A review of earthquake occurrence models for seismic hazard analysis, Probabilistic Engineering Mechanics, 3 (1988), 3–11.
[6] J. G. Anderson and M. D. Trifunac, On uniform risk functionals which describe strong earthquake ground motion: Definition, numerical estimation, and an application to the fourier amplitude spectrum of acceleration, Report CE 77-02 University of Southern California, Los Angeles, U.S.A., 1977.
[7] J. G. Anderson and M. D. Trifunac, Uniform risk functionals for characterization of strong earthquake ground motion, Bulletin of the Seismological Society of America, 68 (1978), 205–218.
[8] A. Ben-Tala, B. Do Chung, S. R. Mandala and T. Yao, Robust optimization for emergency logistics planning: Risk mitigation in humanitarian relief supply chains, Transportation Research Part B: Methodological, 45 (2011), 1177–1189.
[9] C. Boonmee, M. Arimura and T. Asada, Facility location optimization model for emergency humanitarian logistics, International Journal of Disaster Risk Reduction, 24 (2017), 485–498.
[10] A. M. Caunhaye, X. Niau and S. Pokharel, Optimization models in emergency logistics: A literature review, Socio-Economic Planning Sciences, Special Issue: Disaster Planning and Logistics: Part 1, 46 (2012), 4–13.
[11] C. A. Cornell, Engineering seismic risk analysis, Bulletin of the Seismological Society of America, 58 (1968), 1583–1606.
[12] A. Coskun, W. Elmaghraby, M. Karaman and F. S. Salman, Relief aid stocking decisions under bilateral agency cooperation, Socio-Economic Planning Sciences, 2018.
[13] V. Del Gaudio and J. Wasowski, Time probabilistic evaluation of seismically induced landslide hazard in irpinia (southern italy), Soil Dynamics and Earthquake Engineering, 24 (2004), 915–928.
[14] F. Fiedrich, F. Gehbauer and U. Rickers, Optimized resource allocation for emergency response after earthquake disasters, Safety Science, 35 (2000), 41–57.
[15] G. Galindo and R. Batta, Review of recent developments in or/ms research in disaster operations management, European Journal of Operational Research, 230 (2013), 201–211.
[16] R. A. Garrido, Optimal emergency resources deployment under a terrorist threat: The hazmat case and beyond, In Handbook of OR/MS Models in Hazardous Materials Transportation, International Series in Operations Research and Management Science, chapter 8, pages 245–267. Springer, New York, 2013.
[17] R. A. Garrido and P. Lamas, Optimal logistics and transportation decisions for emergency response to natural disasters, In World Academy of Science, Engineering and Technology 76, chapter 8, pages 201–213. WASET, Johannesburg, South Africa, 2013.
[18] R. A. Garrido, P. Lamas and F. J. Pino, A stochastic programming approach for floods emergency logistics, Transportation Research Part E: Logistics and Transportation Review, 75 (2015), 18–31.
[19] I. D. Gupta, Probabilistic seismic hazard analysis method for mapping of spectral amplitudes and other design-specific quantities to estimate the earthquake effects on man-made structures, ISET Journal of Earthquake Technology, 44 (2007), 127–167.
[20] J. Holguín-Veras, N. Pérez, S. Ukkusuri, T. Wachtendorf and B. Brown, Emergency Logistics Issues Affecting the Response to Katrina: A Synthesis and Preliminary Suggestions for Improvement, Transportation Research Record: Journal of the Transportation Research Board, 2022 (2007), 76–82.
[21] E. L. Krinitzsky, Earthquake probability in engineering – part 1: The use and misuse of expert opinion: The third richard h. jahns distinguished lecture in engineering geology, Engineering Geology, 33 (1993), 257–288.
[22] J. Luetchte and S. Ahmed, A sample approximation approach for optimization with probabilistic constraints, SIAM Journal on Optimization, 19 (2008), 674–699.
[23] E. Mas, A. Suppasri, Sh. Koshimura and F. Imamura, Agent based simulation of the 2011 great east japan earthquake tsunami evacuation procedure. introduction to an integrated model of tsunami inundation and evacuation, Journal of Natural Disaster Science, 34 (2012), 41–57.
[24] T. Matisziw, A. Murray and T. Grubesic, Strategic network restoration, Networks and Spatial Economics, 10 (2010), 345–361.
[25] R. K. McGuire, Seismic design spectra and mapping procedures using hazard analysis based directly on oscillator response, Earthquake Engineering and Structural Dynamics, 5 (1977), 211–234.
[26] A. Nemirovski and A. Shapiro, Convex approximations of chance constrained programs, SIAM Journal on Optimization, 17 (2007), 969–996.
[27] L. Ozdamar, D. Tuzun-Aksu, E. Yasa and B. Ergunes, Disaster relief routing in limited capacity road networks with heterogeneous flows, Journal of Industrial and Management Optimization, 14 (2018), 1367–1380.
[28] B. K. Pagnoncelli, S. Ahmed and A. Shapiro, Sample average approximation method for chance constrained programming: Theory and applications, Journal of Optimization Theory and Applications, 142 (2009), 399–416.
[29] B. Papazachos, E. E. Papadimitriou, A. A. Kiratzi, Ch. A. Papaoaonou and G. F. Karakaisis, Probabilities of occurrence of large earthquakes in the aegae and surrounding area during the period 1986–2006, Pure and Applied Geophysics, 125 (1987), 597–612.
[30] B. C. Papazachos, Ch. A. Papaoaonou, V. N. Margaris and N. P. Theodulidis, Seismic hazard assessment in greece based on strong motion duration, Proceedings of the Tenth World Conference on Earthquake Engineering, 2 (1992), 425–430.
[31] T. Parsons, Recalculated probability of m greater than 7 earthquakes beneath the sea of marmara, turkey, Journal of Geophysical Research, 109 (2004), 1–21.
[32] T. Parsons, Significance of stress transfer in time-dependent earthquake probability calculations, Journal of Geophysical Research: Solid Earth, 110 (2005), 1978–2012.
[33] M. Peng, Y. Peng and H. Chen, Post-seismic supply chain risk management: A system dynamics disruption analysis approach for inventory and logistics planning, Computers & Operations Research, Special issue Multiple Criteria Decision Making in Emergency Management, 42 (2014), 14–24.
[34] D. Richardson, S. de Leeuw and I. F. A. Vis, Conceptualising inventory prepositioning in the humanitarian sector, In Luis M. Camarinha-Matos, Xavier Boucher, and Hamudeh Afsarmanesh, editors, Collaborative Networks for a Sustainable World, pages 149–156, Berlin, Heidelberg, 2010. Springer Berlin Heidelberg.
[35] D. A. Richardson, S. Leeuw and W. Dullaert, Factors affecting global inventory prepositioning locations in humanitarian operations—a delphi study, Journal of Business Logistics, 37 (2016), 59–74.
[36] F. S. Salman and E. Yücel, Emergency facility location under random network damage: Insights from the istanbul case, Computers & Operations Research, 62 (2015), 266–281.

[37] J.-B. Sheu, Dynamic relief-demand management for emergency logistics operations under large-scale disasters, Transportation Research Part E: Logistics and Transportation Review, 46 (2010), 1–17.

[38] J.-B. Sheu, An emergency logistics distribution approach for quick response to urgent relief demand in disasters, Transportation Research Part E: Logistics and Transportation Review, 43 (2010), 687–709.

[39] J. Tobita, N. Fukuwa and M. Mori, Integrated disaster simulator using webgis and its application to community disaster mitigation activities, Journal of Natural Disaster Science, 30 (2008), 71–82.

[40] M. I. Todorovska and M. D. Trifunac, Liquefaction opportunity mapping via seismic wave energy, Journal of Geotechnical and Geoenvironmental Engineering, ASCE, 125 (1999), 1032–1042.

[41] S. Tofighi, S. A. Torabi and S. A. Mansouri, Humanitarian logistics network design under mixed uncertainty, European Journal of Operational Research, 250 (2016), 239–250.

[42] H. Wang, L. Du and S. Ma, Multi-objective open location-routing model with split delivery for optimized relief distribution in post-earthquake, Transportation Research Part E Logistics and Transportation Review, 69 (2014), 160–179.

[43] T. Yao, S. R. Mandala and B. D. Chung, Evacuation transportation planning under uncertainty: A robust optimization approach, Networks and Spatial Economics, 9 (2009), 171–189.

[44] E. Yücel, F. S. Salman and I. Arsik, Improving post-disaster road network accessibility by strengthening links against failures, European Journal of Operational Research, 269 (2018), 406–422.

[45] W. Yushimito, M. Jaller and S. Ukkusuri, A voronoi-based heuristic algorithm for locating distribution centers in disasters, Networks and Spatial Economics, 12 (2012), 21–39.

Received September 2018; 1st revision December 2018; 2nd revision February 2019.

E-mail address: rodrigo.garrido@udp.cl
E-mail address: ivan.aguirre@uai.cl