

## STOCHASTIC OPTIMIZATION APPLIED TO THE PRE-POSITIONING OF DISASTER RELIEF SUPPLIES IN BRAZIL

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### ABSTRACT

The increase in the number and magnitude of disasters and, consequently, in the number of victims makes the preparation for these events a necessity in modern societies. This paper proposes a methodology to define locations for pre-positioning disaster relief supplies through a two-stage stochastic optimization model. Based on transportation costs and penalties for unmet demand, a stochastic linear programming model minimizes operating costs and meets the demand to locate distribution centers for pre-positioning disaster relief supplies. Due to the uncertainty of the severity of disasters, the influence of media after disasters and ruptures in highways are represented as scenarios. A detailed analysis on how to assign penalties for unmet demand is also presented. An application in Brazil illustrates the effectiveness of the proposed approach. The results show that stochastic models promote more reliable results than deterministic models, especially in situations where materials available cannot meet all demand.

**KEYWORDS:** humanitarian logistics, facility location, stochastic optimization.

**Main area:** Logistics and Transport.

### 1 Introduction

Climate change has caused several natural disasters in recent years and forecasts estimate that over the next 50 years, natural and man-made disasters will increase fivefold in number and severity (Thomas and Kopczak, 2005). These events and their consequences illustrate how challenging the response to extreme events can be (Holguín-Veras et al., 2007).

The large number of victims and the unpredictable nature of such events make humanitarian operations a critical characteristic of disaster management and one of the main ways to improve the time, cost and quality of relief operations (Blecken et al., 2009). Humanitarian logistics is a combination of preparedness and response (Tomasini and Van Wassenhove, 2009). In the preparedness phase, the activities are a continuous process over the long term, without urgency, especially pre-positioning materials. The response phase is a fast supply process with high level of urgency because the lead time for materials may jeopardize the rescue operation (Kessler, 2013).

Operations in many humanitarian crises still have their management models established on principles of military and governmental organizations, based on the "just in case" philosophy, due to the lack of alternative supply in times of crisis (Natarajarathinam et al., 2009). The increase in the number of people affected by natural (hurricanes, floods, earthquakes, tsunamis)

and anthropogenic (terrorist attack, technological or nuclear accident) disasters has required major management efforts from relief organizations and emergency operation teams. Several studies under a global perspective have been developed to improve this response, demonstrating the importance of logistics in humanitarian operations (Beamon and Kotleba, 2006; Thomas, 2004; Van Wassenhove, 2006).

In Brazil, floods occurred in the South (Itajai Valley) in 2008, in the Southeast (São Luiz do Paraitinga in early 2011, in Espírito Santo in 2013 and debris flow in Itaóca in 2014) as well as catastrophic landslides in Rio de Janeiro in 2011, creating thousands of victims. There are also predictions of increased frequency of these types of disasters as a result of global warming (Marengo et al., 2013; Pinto Jr. et al., 2013). Therefore, preparedness measures are necessary, including location and pre-positioning of relief supplies.

Relief supplies are basic elements for affected people to have access to food and hygiene products in the first moments after the disaster. Agility and readiness in the distribution of these items are necessary, especially in the first 72 hours after the event (Salmerón and Apte, 2010) so that rescue teams can begin the recovery activities, and the victims can thus stabilize their lives. Materials are also required for relief teams (response) to act immediately after the event.

In the network configuration, the strategy for locating relief supplies, along with the humanitarian logistics supply chain, is characteristically relevant to the response time for a disaster (Balcik and Beamon, 2008). Facility location decisions affect the performance of the emergency relief operations in a disaster because the number and location of distribution centers, as well as the amount of relief supplies therein, directly affect the response time and costs incurred along the supply chain.

This paper proposes a methodology to support the decision on where to locate relief supply facilities. An application in Brazil illustrates the effectiveness of the proposed approach. As a result, an analysis of the Brazilian Civil Defense strategy and the current infrastructure for disaster response could be developed. Through a two-stage stochastic optimization model (Dantzig, 1955), sites are evaluated for installing distribution centers (depots) for these materials. This optimization process results in proposing locations that minimize the total operational cost of opening relief supply depots, considering opening costs and penalties for unmet demand. Constraints can be grouped as capacity (storage and transport), available materials (inventory, donations, and purchases) and minimum level of service (minimum fulfilled demand and coverage). The model results are where depots must be opened, the inventory level that each depot should have, the amount of materials to be purchased, and the amount of material to be transported from the warehouse to the demand point and unmet demand.

Uncertainty is a characteristic of disasters and is introduced in the model through scenarios based on disaster severity and magnitude that affect the demand for relief supplies, media coverage that induces the amount of donations sent by the population in general and accessibility ruptures in some highways. Specific characteristics of humanitarian logistics operations such as product allocation that may be purchased under contracts previously negotiated and establishment of constraints for ruptures in the transportation pathways that restricts capacity are presented. Establishing penalties for unmet demand is a subject underexplored in humanitarian logistics. This article also contributes towards setting these penalties based on the model behavior.

The remainder of this text is organized as follows. Section 2 presents the literature review. Next, section 3 presents the mathematical model. The case study is presented in section 4 and the results in section 5. The concluding remarks are given in section 6.

## **2 Literature Review**

In events such as disasters, the application of stochastic optimization is indicated because there is uncertainty in the determination of the model components (Sen and Hagle, 1999). The hypothesis that all model parameters are known deterministically limits their usefulness in planning under uncertainty because, in deterministic models, all the information for the composition of parameters and variables is considered available. The optimal solution of

deterministic models can be unfeasible in the case of disturbance data (Ben-Tal and Nemirovski, 2000). In two-stage models, the decision variables are classified according to their application: before or after the result of a random variable. Decisions that must be taken prior to the random variables are known as the first stage, while those implemented later are the second stage decisions. The decision variables of the first stage are often associated with planning issues and assigned to strategic decisions. Second-stage variables are normally associated with tactical and operational decisions (Higle, 2005). In the second stage, the solution of the problem depends on the solution of the first stage; however, the first stage cannot be solved without understanding the behavior of the second-stage problem (Shapiro et al., 2009). This feature makes the solution of stochastic models more complex than equivalent deterministic models, demanding a greater computational effort and, therefore, a longer time for solving the problem. A characteristic of stochastic models is the representation of uncertainty by scenarios. To establish the scenarios, each possible event for the problem is defined, as well as the probability of occurrence of these events. The parameter values are then set for each scenario (Sen and Higle, 1999).

In humanitarian logistics, stochastic optimization is used to determine the location of warehouses for materials inventory, allocation and distribution of resources for rescue in cases of urban floods. Due to uncertainty, the location problem is formulated as a two-stage stochastic programming model, in which the first stage minimizes the distances, and the second stage performs the allocation of inventory (Chang et al., 2007). Rawls and Turnquist (2010) present a two-stage stochastic model for facility location considering various scenarios that may occur in a disaster, assigning each uncertainty in demand and penalty for unmet demand. Due to the complexity of the problem, the Lagrangian L-shaped heuristic was used for the solution. Rawls and Turnquist (2011) used constraints of quality of service and average distance of deposits up to demand nodes, performing an application in the South of the United States. Later, Rawls and Turnquist (2012) adapted the previous model for dynamic allocation (72 hours in advance) for short-term demands, which ensured meeting 100% of customer service needs. The penalties for unmet demand in the papers of Rawls and Turnquist (2012) range from 10 to 50 times the value of the product. These values showed that for a given problem situation, the change in the value of penalties affects the amount of deposits opened, as well as the total cost, indicating that the subjectivity of this value affects the problem solution.

Noyan (2012) incorporated in Rawls and Turnquist (2010, 2011, 2012) models the risk measurement, also using two-stage stochastic programming, by introducing the concepts of expected value of perfect information (EVPI) and the value of stochastic solution (VSS) in the model structure. Noyan (2012) highlights that the EVPI and the VSS are the two best-known performance measures for the stochastic solution. The EVPI could be understood as the maximal amount the decision maker would be willing to pay for the exact information on future outcomes and is defined as the difference between the solution obtained by the decision maker able to make the perfect prediction (wait-and-see - WS) and the solution obtained solving the problem under uncertainty (recourse problem - RP). The VSS could be interpreted as the benefit expected by taking uncertainty into account or as the loss expected by the decision maker who opted for deterministic modeling using the average stochastic parameters. VSS is defined by the difference between the stochastic solution (RP) and the average solution of the EEV (expected value problem, fixing parameters to average values) (Birge and Louveaux, 1997). The value of the penalty was established as 10 times (in some cases, 5 times) the value of the product. Benders decomposition was used for the model solution. The results showed the importance of risk allocation in locating humanitarian facilities.

Metz and Zabinsky (2010) evaluated the location of the medical supply warehouses and the inventory levels required for each medical source (first-stage decision) and delivery requirements for supplies through a second stage vehicle routing, which disaggregates the strategic information in operational planning. The model captures specific information for each disaster and its possible effects through the use of scenarios evaluating the event preparation, risk, and uncertainty. Salmerón and Apte (2010) propose a two-stage stochastic model in which the decision of the first stage refers to the strategy of locating supply relief facilities, and the second

stage refers to performing activities of transportation necessary to serve the population. The objective function minimizes the number of deaths, and the scenarios set are the uncertainties about the location and severity of the event.

Bozorgi-Amiri et al. (2013) developed a robust stochastic multiobjective programming for logistics in emergency relief environment under uncertainty. In their approach, not only demand but also the cost of supplies, the acquisition process and transport are considered as uncertain parameters. There is also the possibility of a disruption of one of the depots. The objective function minimizes the total cost and penalizes the unmet demand.

Murali et al. (2012) consider a problem of locating capacitated facilities to determine points where medicines against a hypothetical anthrax attack in Los Angeles would be delivered to the population. A special case is formulated as a maximum coverage model and decides the locations where facilities would be open and the supply quantity assigned to each location, considering uncertainty in demand. The results compare solutions using heuristic location-allocation and simulated annealing metaheuristics. For a quantity of 40 facilities to be opened, the location-allocation heuristic performed 89.66% coverage, better performance compared to simulated annealing at 82.45%.

A bi-objective model with stochastic demand was formulated by Tricoire et al. (2012). The objectives are given by (i) costs of opening distribution centers and distribution to the demand points, and (ii) the unmet demand. To solve the integral programming problem, a branch and cut heuristic was used. Real data application in Senegal showed the viability of the approach.

Zhang et al. (2012) approached the issue of secondary disasters that occur after a major natural disaster. Examples of these disasters are the events of Tōhoku, Japan, in 2011, where a nuclear accident occurred after a disaster of seismic origin. Stochastic demands for the first and second disaster were addressed in an individualized manner with different probabilities for each case. The objective function minimizes the rescue costs.

Nolz et al. (2011) formulated a multiobjective optimization problem in the design of a logistics system to ensure the adequate distribution of emergency assistance after natural disasters, when damage to infrastructure can interrupt the delivery of humanitarian aid. The problem is formulated encompassing three objective functions and solved using a genetic algorithm. The first objective function minimizes the risk measures; the second objective function minimizes the sum of the distances between all the inhabitants and their nearest service stations; and the third objective function minimizes the total travel time.

### 3 The mathematical model

The goal of the proposed model is establishing the local installation of one or more permanent distribution centers for storing relief supplies to aid the victims of disasters that may occur in a region. The problem is modeled as a two-stage stochastic optimization model and is based on papers by Mete and Zabinsky (2010) and Rawls and Turnquist (2011). Uncertainty is introduced through scenarios. Specific characteristics of Humanitarian Logistics Operations such as purchases of relief supplies previously negotiated, places for materials screening and capacity warehousing used only in cases of disasters (incidental), disruptions in access routes and coverage, are inserted.

#### 3.1 Nomenclature

Index sets	
I	Candidate distribution centers ( $i \in I$ )
K	Relief supplies ( $k \in K$ )
J	Demand points ( $j \in J$ )
C	Scenarios ( $c \in C$ )
Deterministic Parameters (unit)	
$g_i$	Annual cost of installation and operation of distribution center $i$ (\$)
$e_k$	Amount available of supply $k$ (kg)

$l_{ik}$	Maximum regular storage capacity of $k$ in distribution center $i$ (kg)
$ne_{ik}$	Minimum annual inventory of $k$ in distribution center $i$ (kg)
$qd_{max}$	Maximum number of distribution centers to be opened
$qd_{min}$	Minimum number of distribution centers to be opened
$a_{ij}$	Binary that assumes the value of 0 if the distance is greater than the maximum distance and the value of 1 otherwise (coverage matrix)
$fv_k$	Weight x volume conversion factor ( $m^3/kg$ )
$bigM$	Big auxiliary number, to make purchases of supplies $k$ only if necessary
<b>Scenario-dependent Parameters (unit)</b>	
$ct_{ij}^c$	Transportation cost from distribution center $i$ to demand point $j$ under scenario $c$ (\$/kg)
$w_{jk}^c$	Penalty per unit of $k$ not supplied to demand point $j$ under scenario $c$ (\$/kg)
$dn_{ik}^c$	Amount of donations of $k$ received in distribution center $i$ under scenario $c$ (kg)
$d_{jk}^c$	Demand of $k$ in demand point $j$ under scenario $c$ (kg)
$ac_i^c$	Binary parameter regarding the accessibility of distribution center $i$ (1 - accessible, 0 not accessible) under scenario $c$
$lid_{ik}^c$	Incidental storage capacity of $k$ in distribution center $i$ under scenario $c$ (kg)
$cp_{ij}^c$	Transportation capacity by weight from distribution center $i$ to demand point $j$ under scenario $c$ (kg)
$cv_{ij}^c$	Transportation capacity by volume from distribution center $i$ to demand point $j$ under scenario $c$ ( $m^3$ )
$dmin_{jk}^c$	Minimum demand of $k$ to be supplied at demand point $j$ , under scenario $c$ (kg)
$cot_k^c$	Contractual limit established for purchases of $k$ , under scenario $c$ (kg)
<b>First-stage decision variables (unit)</b>	
$X_i$	Binary equals 1 if a distribution center $i$ is opened, 0 otherwise
$S_{ik}$	Average inventory level of supply relief $k$ at distribution center $i$ (kg)
<b>Second-stage decision variables (unit)</b>	
$T_{ijk}^c$	Amount of $k$ to transport from distribution center $i$ to point of demand $j$ , under scenario $c$ (kg)
$F_{jk}^c$	The unmet demand of $k$ , at point $j$ under scenario $c$ (kg)
$CO_{ik}^c$	Amount of $k$ purchased, allocated in distribution center $i$ , under scenario $c$ (kg)
$CO\_AUX_k^c$	Auxiliary binary variable to make purchases only if $k$ is necessary

### 3.2 Formulation

The first stage of the model is:

$$\min \sum_i g_i X_i + E_c[Q(X, S, c)] \quad (1)$$

Subject to:

$$\sum_i S_{ik} \leq e_k \quad \forall k \in K \quad (2)$$

$$l_{ik} X_i \geq S_{ik} \quad \forall i \in I, k \in K \quad (3)$$

$$ne_{ik} X_i \leq S_{ik} \quad \forall i \in I, k \in K \quad (4)$$

$$\sum_i X_i \leq qd_{max} \quad \forall i \in I \quad (5)$$

$$\sum_i X_i \geq qd_{\min} \quad \forall i \in I \quad (6)$$

$$\sum_i X_i a_{ij} \geq 1 \quad \forall j \in J \quad (7)$$

The objective function (1) minimizes the operating cost of distribution centers plus the expected value of the solution of the second stage function. Constraint (2) establishes that, for an item  $k$ , the amount stored at every distribution center cannot exceed the maximum amount available. Constraint (3) limits the inventory level by the capacity of the distribution center  $i$ , whereas Constraint (4) limits the minimum inventory of item  $k$  to open a distribution center  $i$ . Constraints (5) and (6) limit the number of distribution centers to be opened, and (7) ensures the minimum distance from the point of demand to at least one distribution center  $i$ .

The second stage of the model is formulated as:

$$Q(X, S, c) = \min \sum_i \sum_j \left( ct_{ij}^c \sum_k T_{ijk}^c \right) + \sum_j \sum_k w_{jk}^c F_{jk}^c \quad (8)$$

Subject to:

$$\sum_j T_{ijk}^c \leq S_{ik} + dn_{ik}^c + CO_{ik}^c \quad \forall i \in I, k \in K, c \in C \quad (9)$$

$$F_{jk}^c = d_{jk}^c - \sum_i T_{ijk}^c ac_i^c \quad \forall j \in J, k \in K, c \in C \quad (10)$$

$$(l_{ik} + lid_{ik}^c) X_i \geq \sum_j T_{ijk}^c ac_i^c \quad \forall i \in I, k \in K, c \in C \quad (11)$$

$$\sum_k T_{ijk}^c \leq cp_{ij}^c \quad \forall i \in I, j \in J, c \in C \quad (12)$$

$$\sum_k T_{ijk}^c fv_k \leq cv_{ik}^c \quad \forall i \in I, j \in J, c \in C \quad (13)$$

$$\sum_i T_{ijk}^c ac_i^c \geq dmin_{jk}^c \quad \forall j \in J, k \in K, c \in C \quad (14)$$

$$bigM (1 - CO\_AUX_k^c) > \sum_j d_{jk}^c - \sum_i S_{ik} - \sum_i dn_{ik}^c \quad \forall k \in K, c \in C \quad (15)$$

$$bigM CO\_AUX_k^c \geq \sum_i S_{ik} + \sum_i dn_{ik}^c - \sum_j d_{jk}^c \quad \forall k \in K, c \in C \quad (16)$$

$$CO_{ik}^c \leq bigM (1 - CO\_AUX_k^c) \quad \forall i \in I, k \in K, c \in C \quad (17)$$

$$cot_k^c x_i \geq CO_{ik}^c \quad \forall i \in I, k \in K, c \in C \quad (18)$$

$$cot_k^c \geq \sum_i CO_{ik}^c \quad \forall k \in K, c \in C \quad (19)$$

$$\sum_i CO_{ik}^c \leq \sum_j d_{jk}^c - \sum_i S_{ik} - \sum_i dn_{ik}^c + CO\_AUX_k^c M \quad \forall k \in K, c \in C \quad (20)$$

$$S_{ik}, T_{ijk}^c, F_{jk}^c, CO_{ik}^c \geq 0 \quad \forall i \in I, j \in J, k \in K, c \in C \quad (21)$$

$$X_i, CO\_AUX_k^c \in \{0,1\} \quad \forall i \in I, k \in K, c \in C \quad (22)$$

The objective function (8) minimizes the transportation cost under scenario  $c$  plus penalty for unmet demand under scenario  $c$ . Constraint (9) ensures that the relief supply  $k$  to be transported from  $i$  to demand point  $j$  is available at  $i$ . Constraint (10) calculates the unmet demand for  $k$  in  $j$  under scenario  $c$ . Constraint (11) ensures that relief supply  $k$  being transported from  $i$  to demand point  $j$  is at the distribution center opened by  $x_i$  with sufficient capacity (regular + incidental). Constraints (12) and (13) ensure the transport capacity by weight and volume of supply  $k$ . Constraint (14) ensures that a minimum demand of  $k$  at demand point  $j$  is met. Constraints (15) to (20) are employed for the purchase process: (15) establishes a condition for purchasing relief supplies  $k$  if Demand - Inventory - Donations  $> 0$  ( $CO\_AUX = 0$ ) and (16) defines when no purchase is requested if Inventory + Donations - Demand  $> 0$  ( $CO\_AUX = 1$ ). Constraint (17) defines purchase of relief supply  $k$  only if  $CO\_AUX = 0$ . Constraint (18) ensures that the purchase of supplies  $k$  is allocated to the distribution center opened by  $x_i$ . Constraint (19) ensures that the total purchase of supply  $k$  allocated to each distribution center  $i$  does not exceed the contractual total amount under scenario  $c$ , and (20) ensures that the purchase of supplies  $k$  is performed only after the consumption of the inventory and the donations received in  $i$ . Constraints (21) and (22) define non-negativity and binary variables, respectively.

#### 4 Case study

The optimization model proposed is applied to the case of Paraíba Valley (São Paulo State - Brazil) to evaluate the techniques used and the results. The region, which has two million inhabitants, was chosen because of the historical data and geographic information available and mainly because it is a region prone to natural disasters, as verified in events in the cities of Queluz (2000) and São Luiz do Paraitinga (2010) resulting in over 10,000 displaced persons and minor disasters that frequently occur.

Five local candidates for distribution center location are considered: São Paulo, Caçapava, São José dos Campos, Taubaté, and Tremembé. These sites were chosen because they already have Civil Defense operations and are situated in locations with a history of few accidents, thus less likely to rupture.

The scenarios were established according to the severity and magnitude of disasters (medium, large, and catastrophe). Small disasters were not considered because the community itself overcomes the consequences of a small disaster, thus not requiring relief supplies. In addition, the disclosure in the media was considered in two levels (low or large). The media play a key role, especially in mobilizing volunteers and donations because the media coverage influences the perception of the people of the urgency and people, in natural disasters, are more willing to donate than in man-made disasters (Zagefka et al., 2011). However, the media are organized as for-profit enterprises and carefully choose the most profitable topics (Coronel, 2010), and needs could go unnoticed when the media fail to expose them because of competing headlines. Another consideration is possible disruptions in access routes that may affect the availability of supply channels to affected sites, changing the costs of transport and supplies.

To establish scenarios, probabilities were estimated based in an expert panel on the subject (Salmerón and Apte, 2010). The probabilities were estimated using the Delphi method due mainly to anonymity because, among specialists, there was functional hierarchy, which could influence opinions. Experts in Civil Defense, Disasters, Geology, Meteorology, Architecture, and Journalism composed the panel. Table 1 shows the probabilities of the scenario.

Disclosure	Disaster magnitude		
	Medium	Large	Catastrophe
Low dissemination by media	24.00%	8.11%	1.00%
High dissemination by media	26.44%	15.33%	7.33%
High dissemination by media and with access ruptures	0.00%	13.56%	4.22%

Table 1 - Probability of scenarios

The parameters were set based on information from the Civil Defense, which has historical data about materials and transportation since 1999, available government budgets, risk maps, international guidelines, academic and field activities. To calculate the demand ( $d_{jk}^c$ ), the materials were defined based on The Sphere Project (2011) and UNHCR (2007) guidelines. The materials were divided into materials for the population in need that could be for individual use (ex. clothes) or for household use (estimated from 4 persons per household – ex. cleaning kit) and materials for the response teams (ex. tools). The quantities for the population in need were considered using two axes: the Civil Defense historical data and the risk mapping conducted by municipalities that comprehend the number of households in a vulnerable situation and, the other axis, according to the magnitude of a disaster multiplied by a weighting value (Balcik and Beamon, 2008). The quantities for the response teams were calculated based on the size and risk of the city.

### 5 Results and discussions

A careful analysis on penalties was conducted. Penalties for not meeting demand is established for a model calibration (Metz and Zabinsky, 2010), verifying the impact of this value on results. Unlike costs such as transportation, purchases and warehousing, there is no effective payment of the penalties, despite having a monetary unit, causing a characteristic of immateriality in an analysis by a decision maker. In this work, the main goal of this calibration is to assure that shortages occur only due to the model constraints, preventing viable non-supply, not producing unwanted results, as well as providing penalty values in accordance with other resulting costs.

Rawls and Turnquist (2010, 2011, 2012); Noyan (2012); Metz and Zabinsky (2010) and Bozorgi-Amiri et al. (2013) link penalties to the value of the product. Initially in this work, penalty is set as the same for all products, and the transportation cost was chosen as the initial reference. The highest transportation cost between locations was initially set as the lower limit because below this value, the model may allow shortages in the location because the cost of supply is smaller than the transportation cost. Based on growing values, the model was tested, and the results behavior was observed from 1 to 10,000 times the highest transportation cost. The high value for the upper limit is assigned to verify the behavior of the model in this range of values, the same way as done by Barbarosoglu and Arda (2004), especially regarding unmet demand and values of EVPI and VSS. Figure 1 illustrates the behavior of total open deposits and the shortages due penalties.

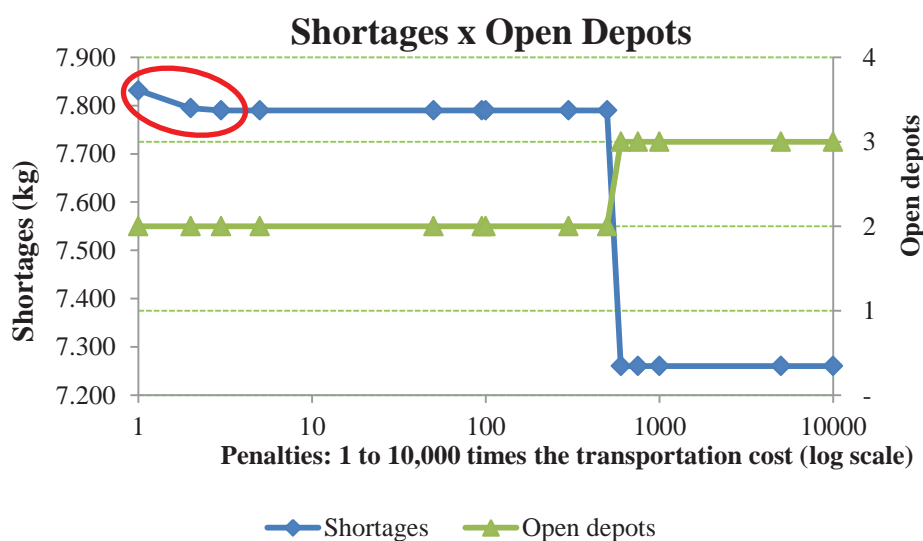


Figure 1 – Open depots and penalties

Note that even in the range of 1-3 times the highest transportation cost (highlighted area), the model allows shortages. Consequently, 3 times higher transportation cost was the lower limit



set for penalties. From this value, the unmet demand remains stable until one more depot is opened, which occurs between 500 and 600 times. These findings indicate that even at this level there were constraints preventing available materials from being used. In this case, the constraint was the sum of incidental and storage capacity.

As shown in Figure 2, the EVPI, from 95 times the highest transportation cost, has an upward trend and then falls again because the WS solution for calculating the EVPI opens depots by scenarios. From penalty equal to 95 times the highest transportation cost, in some scenarios depots are opened, increasing the difference in fixed costs between the solution obtained under uncertainty (recourse problem - RP) and the WS solution. This number of opened depots increases until the third depot is opened by stochastic solution (RP). From this point, the decline of percentage value of EVPI (absolute value remains) is observed. The VSS has a logarithmic trend with variations in this trend at the points of open depots because in all the cases, the deterministic solution opens only 2 depots. Figure 2 shows the behavior of total open deposits (RP solution) and EVPI and VSS.

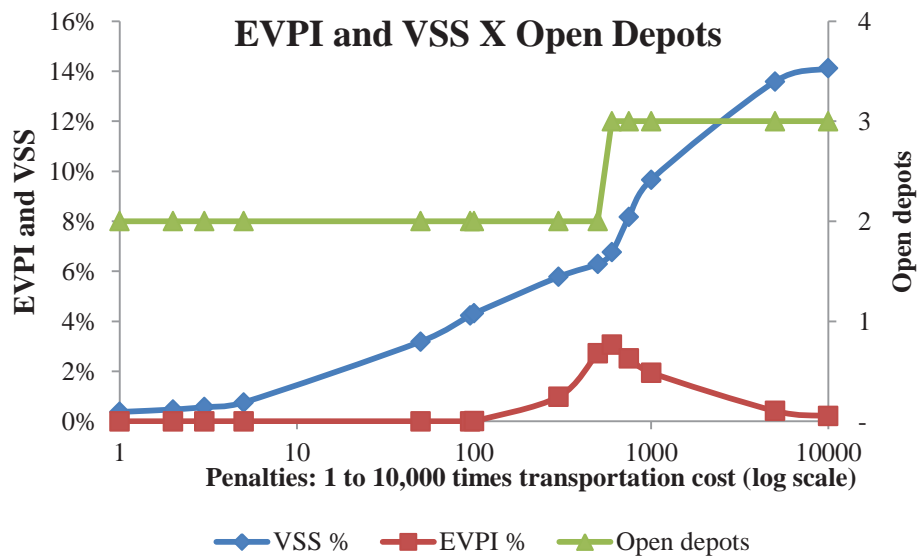


Figure 2 – VSS and EVPI and open depots.

The penalty between 3 and 95 times the maximum value of transportation cost can be assumed to produce equivalent results. For further analysis, we set this value at 95.

The model was implemented using the software AIMMS 3.13, CPLEX solver 12.5 Intel Core 2 Quad® Q9650 CPU 3GHz, 4 Gb RAM, 32-bit operational system Windows7®. To solve all the instances (RP, WS, deterministic and EEV), the time was 39 s.

The deterministic solution was obtained using the weighted average of the parameters to a 5-year horizon. Different from the deterministic solution, the stochastic solution shows the values obtained and also shows that the penalties (for 95 times the transportation cost) strongly influence the results due to the shortage of materials. Table 2 shows the results of deterministic and stochastic models.

	Deterministic (\$)	Stochastic (\$)
Fixed Cost to open depot	80,864.64	80,864.64
Transportation costs	17,388.57	17,957.34
Penalties costs	4,171.08	149,019.97
Total cost	102,424.29	247,841.94
Distribution centers opened	São Paulo	São Paulo
	Tremembé	Tremembé

Table 2 - Results of the deterministic and stochastic models

Shortages occurred in all the scenarios due to unavailable materials or constraints. In scenarios of large disasters and catastrophe, albeit pre-positioned, purchased materials and donations were enough to supply, yet they were not completely used due to constraints on capacity of deposits.

The variation in results from transportation costs and penalties occurs mainly due to differences between demands. While the deterministic model considers the weighted average of scenario demands, the stochastic model considers the supply for all scenarios, including those with large numbers of victims, and the amount of shortages in these scenarios is greater causing a higher amount of penalties. In both situations, the two opened depots are the same, due to the minimum distance constraint.

The result for EVPI was 0.01% and for the VSS 4.23% for penalties equal to 95 times the highest transportation cost. In the worst case, when the penalty is 600 times the highest transportation cost, EVPI was 3.07%. Based on these values, good results are provided to EVPI in accommodation of the uncertainties. The behavior of VSS is compatible with the Humanitarian Logistics literature because the VSS value depends on and increases in the function of the value of the penalties. Similar behavior of VSS was also obtained by Noyan (2012), who achieved 54.05% to 58.42% for EVPI and 0.84% to 5.41% for VSS and Salmerón and Apte (2010), who obtained approximately 25% for EVPI and 47% for VSS. These percentage values are relative to the wait-and-see solution.

## 6 Conclusions

Based on papers by Mete and Zabinsky (2010) and Rawls and Turnquist (2011), this work presented a problem of pre-positioning of disaster relief supply Decisions in Brazil through stochastic modeling. Specific features of the humanitarian operations emergency purchases and disruptions in access routes were added to the model. The model performance was evaluated and presented good results for the accommodation of uncertainties assessed by EVPI in comparison to Noyan (2012) and Salmerón and Apte (2010). One approach to assigning penalties based on the behavior of the model through EVPI and VSS measures was also performed.

The results show that, in this Brazilian case, material availability for major disasters and catastrophes is an issue, and the purchase budgets need to be increased for responding to disasters. As the magnitude of the disaster increases, not only the materials availability but also the coordinated actions and decision-making should be more effective. Transportation planning and locations that allow logistics activities such as screening and storage of materials to respond to a disaster are also necessary.

Considerations about human suffering (Holguin-Veras et al., 2013) and for variation of parameters (Balcik and Beamon, 2008) were performed to analyze the behavior of the model in these situations. The findings also provide an analysis of The Brazilian Civil Defense (Brazil, 2012) that is structured based on the municipal level without a regional approach. The preparedness and response plans are arranged by the cities; however, as assessed by the model, in major disasters and catastrophes, physical structures in affected cities could be disrupted, as observed in the disasters in São Luiz do Paraitinga in 2010 and in the Rio de Janeiro in 2011. A regionalized approach to the strategic plans for disaster preparation and response, encompassing more alternatives of supply points and including mutual assistance between cities, is recommended.

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