Insights from two-stage stochastic programming in emergency logistics

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ABSTRACT

This paper discusses the practical aspects and resulting insights of the results of a two-stage mathematical network flow model to help make the decisions required to get humanitarian aid quickly to needy recipients as part of a disaster relief operation. The aim of model is to plan where to best place aid inventory in preparation for possible disasters, and to make fast decisions about how best to channel aid to recipients as fast as possible. Humanitarian supply chains differ from commercial supply chains in their greater urgency of response and in the poor quality of data and increased uncertainty about important inputs such as transportation resources, aid availability, and the suddenness and degree of "demand". The context is usually more chaotic with poor information feedback and a multiplicity of decision-makers in different aid organizations. The model attempts to handle this complexity by incorporating practical decisions, such as pre-allocation of emergency goods, transportation policy, fleet management and procurement, in an uncertainty environment featured by a scenario-based approach. Preliminary results based on the floods and landslides disaster of the Mountain Region of Rio de Janeiro state, Brazil, point to how to cope with these challenges by using the mathematical model.

Keywords

Emergency logistics, disaster relief, two-stage stochastic programming, scenario generation, floods, landslides, disaster in Rio de Janeiro

INTRODUCTION

A disaster event can severely damage production-distribution systems (Scott and Marshall, 2009, p. 180-181), urgently requiring efficient emergency management practices in an attempt to return the affected community to “normality”' in the sense of the reestablishment of the routine that was in place before the disaster. By recognizing a disaster as a temporal event, some authors (Al-Madhari and Keller, 2007; Carter, 2008; Scott and Marshall, 2009) characterise it as having typical phases that occur before (pre-event) and after (post-event) the disaster strikes. Both the pre-event and post-event phases involve many activities related to logistics planning and supply chain design, e.g., the construction of emergency operations centers (location), the maintenance of emergency supplies (prepositioning), the supply of emergency commodities (transportation), etc.

Although transportation in commercial supply chains is not necessarily a challenging process, quickly providing emergency relief and supplies to the victims of disasters is a hugely complex process fraught with many challenges. In most disaster situations, there is uncertainty about the exact nature and impact of the disaster; a lack of reliable information about the location, numbers and needs of victims; precarious transport links, often made worse or impassable by the disaster; and a scarcity of resources such as transport and warehousing capacity. In order to respond to disasters effectively, governments and humanitarian organizations need to consider all these difficulties when making emergency plans, designing relief supply chains, and operating them during relief operations. However, recent poorly managed humanitarian operations have been evidenced to the world that the implemented response decisions are far from ideal.

Our aim in this research is thus to propose a mathematical stochastic network-flow model to be used within information system frameworks in disaster relief situations. The model can help organizations identify the best allocation of emergency aid goods in warehouses and the most suitable fleet of vehicles as a part of the logistics planning prior to disasters. In addition, given these prior allocations, the model also determines fast response decisions regarding the distribution of supplies to relief centers, inventory, unmet demand and procurement. The total cost of hiring vehicles, distribution and procurement have to fall within a limited budget. Based on real-world problems, our model copes with highly uncertain demands, supplies, donations and arc capacities. The uncertainty is incorporated into the stochastic model via a finite set of reasonable scenarios which, in the illustrative example below, are generated using real data from the January 2011 series of floods and landslides in Rio de Janeiro state, Brazil. Our motivation in analysing the Brazilian context is the recurrent types of disasters that have been occurring in many areas of the country, in particular climatological disasters in Rio de Janeiro. Obviously, the great impact of these events in the communities – in terms of affected people and financial damaged – is consequence of unsolved social problems, but this topic is beyond the subject of this paper.

Our work is related to the work of Özdamar et al (2004); however, whereas they consider a deterministic model, we adopt a more practical view by assuming stochastic data and proposing a systematic manner to generate the scenarios. Other papers similar to ours deal with uncertainties, but in a static decision-making context, for example, Haghani and Oh (1996) and Lin et al. (2011). A deep literature review concerning mathematical models/quantitative decision making in humanitarian logistics and disaster relief can be found in Caunhye et al. (2012), Ortuño et al. (2013), among others.

The rest of the paper is organized as follows. The next section provides a brief description of the mathematical model and discusses the scenario generation method. After, we present some preliminary results and conclude with possible directions for future work.

DESCRIPTION OF THE MATHEMATICAL MODEL

The model now developed comprises the transport of emergency aid supplies among nodes, but can be easily adapted to the evacuation of people from affected areas to relief centers. We assume that the network can be split into relief centers nodes (RC) and warehouse nodes (W). The former represent the nodes with demands, and the latter, the nodes without demands. Since the relief centers are usually adapted facilities, such as schools, churches, etc., we assume that both pre-allocation of stocks and supplies are not allowed in these type of nodes, but that procurement of goods only arises in RC. In addition, there is a maximum number of vehicles that can be hired, as well as a limited amount of stock to pre-allocate and a very restrictive procurement of supplies. Vehicles have both weight and volume capacities (in order to deal with all possible types of emergency goods), and any unused budget in a period can be used in the next period without monetary loss. The aim of the model is minimize the total cost incurred in pre-allocation of stock, inventory and unmet demand over multiple scenarios, as follows:

$$\text{Minimize} \sum_{c=1}^{C}\sum_{n=1}^{N}\alpha_{cn}\cdot P_{cn}^{0}+\sum_{c=1}^{C}\sum_{n=1}^{N}\sum_{t=1}^{T}\sum_{s=1}^{S}\pi_{s}\cdot\left(\beta_{cn}\cdot I_{cnts}+\gamma_{cn}\cdot U_{cnts}\right), \quad (1)$$

where

- α_{cn}, β_{cn} and γ_{cn} represent the unit cost due to pre-allocation of stock, inventory and unmet demand over commodities and nodes, respectively.

- π_s is the probability of occurrence of scenario *s*.
- P_{cn}^0 is the amount of pre-allocated commodity *c* at node *n* (first-stage decision variable).
- I_{cnts} and U_{cnts} are defined as inventory and unmet demand of commodity *c* at node *n* in time period *t* and scenario *s*, respectively (second-stage decision variables).

The model's algebraic constraints are not formulated here but represent the following logical conditions:

1) Flow balance in relief centers for all scenarios.
2) Flow balance in warehouses for all scenarios.
3) Maximum available amount of pre-allocate stock.
4) Maximum number of vehicles that can travel across (damaged) arcs between two nodes for all scenarios.
5) Utilization of the fleet of vehicles based on their volumes for all scenarios.
6) Utilization of the fleet of vehicles based on their weights for all scenarios.
7) Maximum amount of procurement in relief centers for all scenarios.
8) Monetary budget balance for all scenarios.
9) Domains of the decision variables, both first-stage {pre-allocation of stock, number of vehicles} and second-stage {transportation flows, inventory, unmet demand, procurement, unused budget}. Only the number of vehicles is considered an integer variable; the remaining ones are continuous positive.

SCENARIO GENERATION SCHEME

We used the recorded data from the floods and landslides disasters in Rio de Janeiro state, Brazil. These data are available in the Emergency Events Database (EM-DAT, available at www.emdat.be) and correspond to 21 disasters from 1966 to 2013. With this information, we classified each disaster according to the scale system proposed by Eshghi and Larson (2008). The scale system is based on the number of fatal and affected victims of a particular disaster.

To determine the scale of the disaster, we first calculate a number (ϕ) that represents its impact, according to the following expression given in Eshghi and Larson (2008):

$$\phi = Max\left\{\frac{(F-L_F)}{U_F} + logL_F, \frac{(A-L_A)}{U_A} + logL_A - 1\right\}, \quad (2)$$

where F, L_F, U_F, A, L_A, U_A represent, respectively, the number of fatal victims, the corresponding lower and upper bounds (given in Table 1), the number of affected victims, and both bounds. For example, suppose a disaster causes 74 fatal victims and 1,500 affected victims. Then, the number of fatal victims is in the first interval given in Table 1 and the number of affected victims falls within the second interval, which gives F=74, L_F=10, U_F=100, A=1,500, L_A=1,000, U_A=10,000, and

$$\text{Impact } \phi = Max\left\{\frac{(74-10)}{100} + log10, \frac{(1{,}500-1{,}000)}{10{,}000} + log1{,}000 - 1\right\} = 2.1$$

Secondly, we associate this value of ϕ to the corresponding scale of disaster. In this case, we have a crisis situation.

Fatal victims range	Affected victims range	Impact (ϕ)	Scale of disaster
$F \in (10{,}100]$	$A \in (100{,}1.000]$	$1 \le \varphi < 2$	Emergency
$F \in (100{,}1.000]$	$A \in (1.000{,}10.000]$	$2 \le \varphi < 3$	Crisis
$F \in (1.000{,}10.000]$	$A \in (10.000{,}100.000]$	$3 \le \varphi < 4$	Minor
$F \in (10.000{,}100.000]$	$A \in (100.000{,}1.000.000]$	$4 \le \varphi < 5$	Moderate
$F \in (100.000{,}1.000.000]$	$A \in (1.000.000{,}10.000.000]$	$5 \le \varphi < 6$	Major
$F \in (1.000.000, \infty)$	$A \in (10.000.000, \infty)$	$6 \le \varphi$	Catastrophe

Table 1. Ranges for the overall victims and scale of disaster (Source: Eshghi and Larson, 2008).

The classification of the scale of disaster in Rio de Janeiro state is illustrated in

Table 2. We then used the relative frequency for each scale of disaster to estimate the corresponding probability of occurrence, as shown in Table 3.

Disaster	Fatal victims	Affected victims	Scale of disaster
1	350	4,000,000	Crisis situation
2	256	74,938	Minor disaster
3	74	1,000	Emergency
4	9	50,953	Minor disaster
5	11	15,400	Minor disaster
6	9	50,953	Minor disaster
7	6	2,272	Crisis situation
8	59	200,080	Moderate disaster
9	29	16,000	Minor disaster
10	7	2,000	Crisis situation
11	74	1,500	Crisis situation
12	4	200,000	Moderate disaster
13	256	74,938	Minor disaster
14	2	2,000	Crisis situation
15	30	1,510	Crisis situation
16	74	1,000	Emergency
17	25	1,000	Emergency
18	918	32,036	Minor disaster
19	7	800	Emergency
20	289	3,020,734	Major disaster
21	67	2,300	Crisis situation

Table 2. Classification of the disasters in the state of Rio de Janeiro from 1966 to 2013 (Source EM-DAT).

From Table 2, it is clear that the probability of occurrence for each scale of disaster is 4/21, 6/21, 6/21, 3/21, 2/21 and 0 – from an emergency situation to a catastrophe, respectively. The number of victims that need emergency supplies is assumed to be 10.96% of the average total number of victims (affected and fatal) for each scale of disaster. This figure is the real percentage of affected people in the disaster of the Mountain Region of Rio de Janeiro state in January 2011. Not knowing the daily number of victims, we also implement a random number generator that tries to simulate the dynamic daily demand in disaster relief situations: suddenly-occurring demand in very large amounts and short lead times for a wide variety of supplies contrast with periods of low demand (Sarkis et al., 2009).

Note that so far we have only determined the scenarios for the stochastic demand (D). We also need to evaluate scenarios for the remaining parameters, supply (S), donation (Do) and arc capacity (C). We assume that the scenarios for these parameters are associated with the scale of disaster, as follows (Alem and Clark, 2015):

"Construct one scenario with the same impact of the current demands' scenarios; one scenario in which the impact of the disaster is one level above the current demands' scenarios; and one last scenario in which the impact of the disaster is one level below the current demands' scenarios. For example, consider a moderate disaster scenario for demands. Then, the pair (supply, donation) can be materialized as a minor disaster (one level below) or as a major disaster (one level above), and so forth".

This procedure is based on the assumption that it is not possible to ensure that the supplies, donations and network structure (arc capacity) follow exactly the impact of the disaster. We feel that they do not have a completely different behavior, but they do not have necessarily exactly the same behavior. Finally, we assume statistical independence among the stochastic parameters. Our resulting 40 scenarios were ordered in such manner that the impact of the disaster increases as their correspondent number increases.

Implementation Details

In order to solve the proposed model and validate it, we construct instances based on the disaster of the Mountain region of Rio de Janeiro in 2011. We tried to use real data as much as possible, but we also had to estimate the unavailable information. The motivation in using this disaster as an example is due to its impact: more than 900 fatal victims and 30,000 homeless and displaced people. In fact, the disaster is now considered the largest disaster already recorded in Brazil due to the number of deaths. The instances assumed 7-days-long periods, 9 relief centers, 4 warehouses, 3 types of vehicles, 6 emergency aid goods and 40 scenarios. For reasons of brevity, we will not provide the detailed dataset, but the reader is refereed to Alem and Clark (2015) for a complete discussion. The mathematical models were implemented in GAMS and solved with CPLEX 12.5. The experiments were carried out on a Core-i7 notebook with 8 GB of memory running.

Preliminary Results

Figure 1 shows the flows between the warehouses and the following affected areas: Teresópolis (TRS), Petrópolis (PTP), Nova Friburgo (NFB), São José do Vale do Rio Preto (SVRP), Bom Jardim (BJD), Sumidouro (SMD), Areal-Sapucaia-Três Rios (AST), Santa Maria Madalena (SMM) and São Sebastião do Alto (SSA). The warehouses are located in Teresópolis (TRS-D), Petrópolis (PTP-D), Nova Friburgo (NFR-D) and Rio de Janeiro city (RJ-D). By using more than 1,000 trucks and 7 helicopters, it was possible to deliver all emergency goods with reasonable service levels. There is a clear concentration of flows leaving RJ-D and a small amount of flows arriving in the most distant nodes, e.g., SSA and SMM. The transportation across the different scenarios should increase as demand and supply increase; however, due to the limited budget, the experienced increase in transportation is not sufficient to meet demands in most pessimistic scenarios. In fact, the service level analysis (based on the cumulative unmet demands over goods and nodes in the last period of the horizon) revealed that only up to 12% of demand is met in the worst scenario (Figure 2).

Amongst other insights, our preliminary results confirmed: (a) the importance of pre-allocating emergency supplies before disaster strikes in an attempt to reduce lead times and thus improve service levels; (b) that it is vital to have a diversified fleet to reach distant or collapsed areas; (c) although much more expensive, procurement in relief centers nodes could be an alternative strategy to fulfill more demands, so it might be worth making arrangements between organizations and local vendors to increase procurement in difficult access areas; (d) after the disaster strikes, it is crucial to rapidly make funds available to increase the effective response, otherwise even the most efficient logistics planning will fail to achieve fairness in the distribution of emergency supplies. In effect, see in Figure 3 the remaining monetary budget across the proposed 40 scenarios (dotted line related to the secondary scale in %). Practically, the budget is used in all scenarios; in worse scenarios, we observe that there is a larger amount of money to the humanitarian operations, but this amount is not sufficient to cover all the expenses.

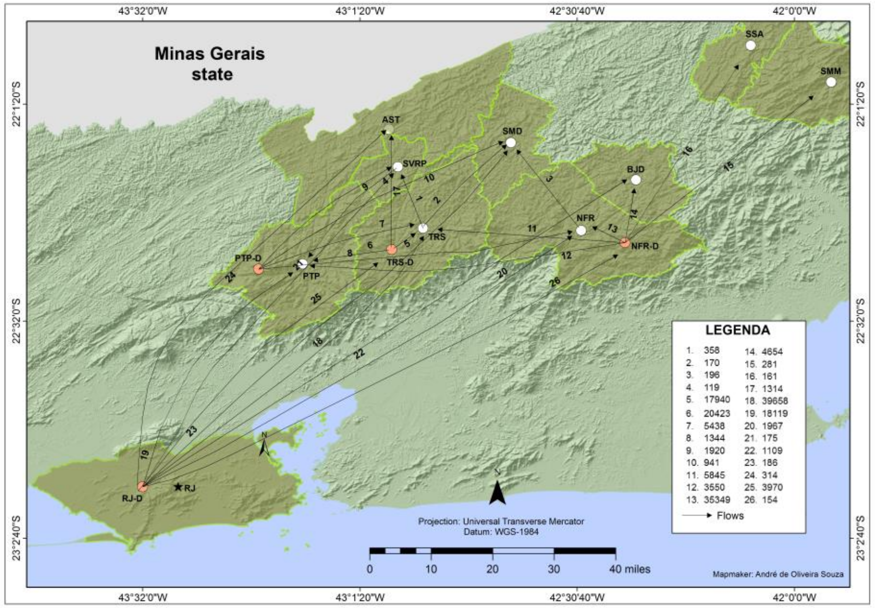

Figure 1. Flows of goods in between relief centers and warehouses.

CONCLUSION

Motivated by the recurrent number of floods and landslide disasters in Brazil and worldwide, and by the lack of engineering-type management and support in the response, we proposed a new two-stage stochastic programming model for logistics planning in disaster relief. Our model takes into account many practical constraints and helps to identify optimal (or near-optimal) strategies in both preparedness and response under a myriad of different scenarios, which reflect some uncertainties that typically arise in disaster settings. We applied the model to the humanitarian operations of the disaster in the Mountain Region of Rio de Janeiro in 2011, as it is now considered the worst disaster ever in Brazil regarding the number of fatalities Although we tried hard to design a representative instance, we had to make many assumptions to estimate unavailable data. Taking account of the aforementioned insights, future research will propose a more integrated mathematical model to help coordinating location, distribution and budget allocation from a humanitarian logistics perspective. Also, we plan to evaluate the impact of the uncertainty in this problem by using well-known concepts in stochastic programming: the expected value of perfect information (EVPI) and the value of stochastic solution (VSS).The motivation is to find (deterministic) strategies that perform as good as stochastic ones in the presence of uncertainty, and use them into the model to evaluate more efficiently large-scale instances within a reasonable amount of time.

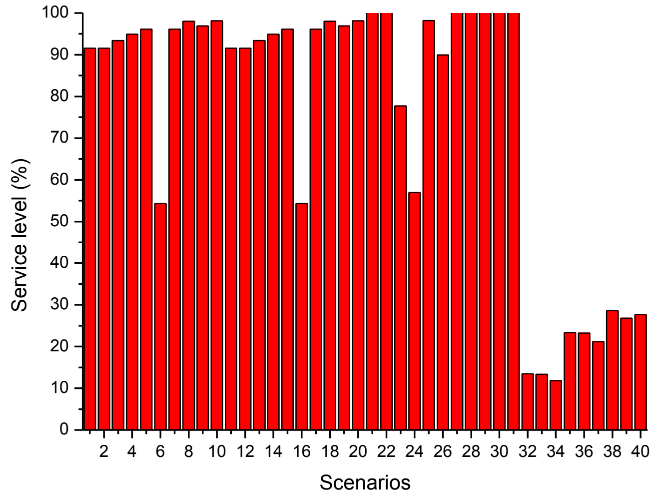

Figure 2. Service level (%) in each scenario.

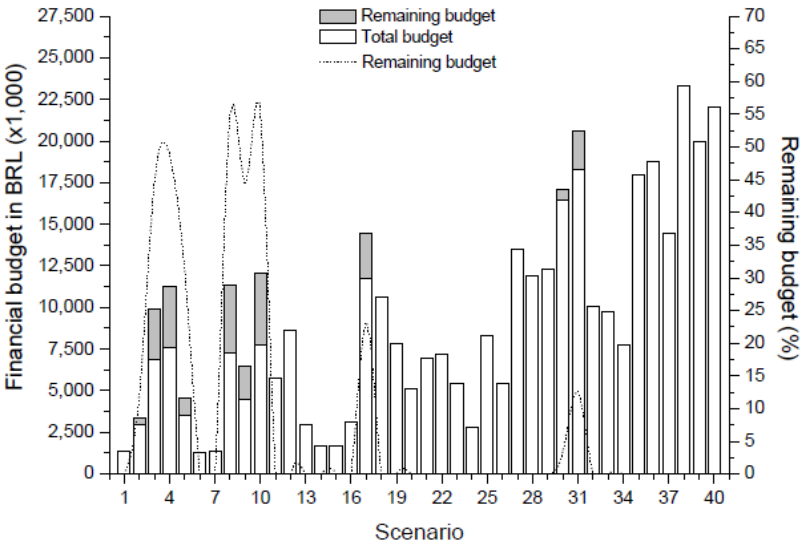

Figure 3. Monetary budget across the proposed scenarios.

ACKNOWLEDGMENTS

The first author offers thanks for grant 2013/08303-2 from the São Paulo State Research Support Foundation (FAPESP) and grants 470154/2013-6 and 306237/2014-8 from the Brazilian National Council for Scientific and Technological Development (CNPq). Both grants are gratefully acknowledged.

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