Strategies to Optimize the Impact of Supplies Distribution in Post-disaster Operations

Christophe Duhamel[1], Daniel Brasil[2,3], Andréa Cynthia Santos[2]
Éric Châtelet[4] and Babiga Birregah[4]
[1]*LIMOS-UBP, Université Blaise Pascal, Aubière, France*
[2]*ICD-LOSI, Université de Technologie de Troyes, Troyes, France*
[3]*DCC-UFMG, Universidade Federal de Minas Gerais, Belo Horizonte, Brazil*
[4]*ICD-LM2S, Universié de Technologie de Troyes, Troyes, France*

Keywords: Post-disaster Response, Logistics, Distribution, Resilience, Heuristics.

Abstract: We consider the problem of setting a supplies distribution system in a post-disaster context. The primary decision variables correspond to the site opening schedule and the secondary variables focus on the supplies distribution to the population zones. The objective is to optimize the supply delivery to the population, while satisfying some logistics restrictions, both human and financial. We present a non-linear model and we propose a decomposition approach. The master level problem is addressed by NOMAD solver. The slave subproblem is treated as a black-box and it is solved by a combination of two heuristics and a VND local search. Numerical results on both random instances and on one realistic instance, using several scenarios, shows our approach provides satisfactory results.

1 INTRODUCTION

Recent disasters have shown the critical importance of setting both a fast, fair and efficient post-disaster response, especially in terms of supplies distribution. However, those criteria are often hard to satisfy in practice due to the limited information, to uncertain data, to conflicting decisions, to limited time among others (Boin and McConnell, 2007). Moreover, many areas exposed to natural disasters have structurally poor infrastructures and high densities of population. Hence, providing an efficient response and overcoming the logistic challenge is vital to mitigate the risks, to reduce the impact over the population and to improve the recovery process.

Resilience plays a key role in crisis management, and especially in the humanitarian context. Several main approaches have been proposed for modeling the resilience, among them the PR^2 (Preparedness, Response (or Reactiveness) and Recovery) and the R^4 (Robustness, Resourcefulness, Redundancy and Rapidity) models. The PR^2 model (Bruneau and Reinhorn, 2007; Haimes, 2009; Mezzou et al., 2011) aims at quantifying three criteria: the system preparedness, its response and its recovery. Preparedness refers to anticipation strategies, before the perturbation (the disaster) occurs. The response encompasses the immediate measures applied to overcome the perturbation while the recovery corresponds to the operations for restoring the system. The R^4 model (Bruneau et al., 2003) uses four criteria: the robustness, the resourcefulness, the redundancy and the rapidity. The robustness quantifies the system's ability to absorb the perturbation and the redundancy details the components able to partially keep the system operational. The resourcefulness is the ability to perform supplies deployment and the rapidity is the system's ability to return to its initial state. Those two models are illustrated on Figure 1

In the context of humanitarian aid, those models have to be adapted in order to integrate the human side of socio-technical systems. The resulting proposed model is shown in Figure 2.

Our work takes place in this adapted model in which the monitored performance is the size of the population in an humanitarian system. We consider the problem of organizing the best possible way a supplies distribution system in order to reach and help as much population as possible, while satisfying some resource limitations. The objective is to optimize the

Duhamel C., Brasil D., Cynthia Santos A., Châtelet E. and Birregah B..
Strategies to Optimize the Impact of Supplies Distribution in Post-disaster Operations.
DOI: 10.5220/0004927703420349
In *Proceedings of the 3rd International Conference on Operations Research and Enterprise Systems* (ICORES-2014), pages 342-349
ISBN: 978-989-758-017-8

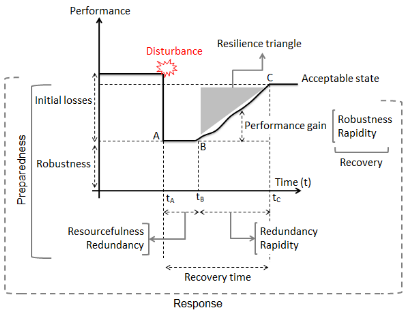

Figure 1: The R^4/PR^2 resilience model.

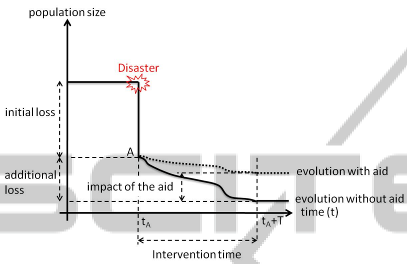

Figure 2: Our adapted resilience model.

impact of the aid on the population, considered here as the population survivability. We propose a mathematical formulation and heuristics which couple a local search with a non-linear solver, NOMAD (Le Digabel, 2011).

This work is organized as follows: a bibliographical review is done in the next section. Section 3 introduces the problem followed by a mathematical model description. The proposed method is presented in Section 5. Preliminary numerical results are shown in Section 6, before concluding remarks.

2 RELATED WORKS

Quantitative models for designing the humanitarian logistics have been proposed recently in (Rottkemper et al., 2012; Berkoune et al., 2012; Nolz et al., 2010). They focus on two key components: the location of warehouses and the routing system. Aside from the theoretical hardness of those core problems, additional features are also considered. Both the uncertainty on the data (Rottkemper et al., 2012) and various evaluation criteria (Nolz et al., 2010) increase the overall complexity of the problem. (Berkoune et al., 2012) propose a decision support system to be used in crisis situations. They consider three major decisions to be made. The first decision stands for the number of sites to be opened. The second relies on the aid that will be provided in each site. And third, how the aid will be distributed. The objective is to minimize the deployment time. They solve the models with a branch-and-bound algorithm using CPLEX, and compare the solutions in terms of quality of solution and computational time. This approach has recently been extended in (Abounacer et al., 2014) in which an exact method is proposed to solve the problem of locating facilities and providing a distribution network under several criteria.

The multi-criteria humanitarian aid distribution problem where the transportation network is subject to reliability issues is considered by (Vitoriano et al., 2011). Several criteria are modeled: cost, duration, equity, priority, reliability and security. They are aggregated in a goal-programming approach using GAMS and Cplex solver. This method is then evaluated on data about the Port-au-Prince earthquake catastrophe. The work has been extended in (Liberatore et al., 2014) by taking into account both the transportation network restoration (roads and bridges) and the supplies distribution. Six criteria are used: maximal arrival time, total served demand, maximal ransack probability, global security, minimal arc reliability and global network reliability. The resulting proposed RecHADS model aims at finding the best infrastructure recovery plan while providing supplies to the population. The coordination of the network restoration and the aid distribution subproblems on the same instance as before is shown to provide better global solution than a sequential approach where a better final network is preferred over a better distribution.

The problem of multi-criteria warehouse location-routing problem has been addressed by (Rath and Gutjahr, 2014) for disaster relief. It consists in locating warehouses and designing vehicles routes to deliver supplies to the population. Three criteria are considered: the opening costs, the distribution costs and the demand covered. A matheuristic combining a Mixed-Integer Linear Program with a Variable Neighborhood Search is proposed and compared with the Non-dominated Sorting Genetic Algorithm II.

Some works have been focused on routing and distributing supplies to clusters areas as in (Prins et al., 2012; Afsar et al., 2012; Afsar et al., 2014). The authors deal with a medium-long terms macro distribution. Some hypothesis have been considered such as the center sites distribution are known in advance and thus demands are leaved in a central facility for each clusters. Moreover, a fleet of vehicles is used, but the number of available vehicles is unknown *a priori*. Even if the authors do not focus on the benefits of such distribution in a resilience system, it may contribute in a medium-to-long term recovery phase. Very sophisticated heuristics and exact methods are proposed to solve the mentioned problem.

3 PROBLEM DEFINITION

In this work, we consider the problem of setting a distribution system in order to deliver supplies to the population. Two sets of decisions have to be taken: first, where and when to open distribution centers and second, how much, when and where to send supplies. The distribution centers play a critical role as they define an intermediate layer between the supplies arrival point (a port or an airport for instance) and the population. Their location must be carefully chosen in order to be as close as possible to the population, thus limiting the logistic distance. The set of potential distribution centers typically includes safe buildings able to store the supplies and to ensure vehicles arrival/departure, for instance warehouses, stadium, schools.

Choosing the right set of distribution centers is a difficult task as it involves several criteria. Besides, some centers could be first open at some locations and later transferred to other locations. Here, we consider only the first part of the humanitarian delivery of supplies. Thus site relocation is not allowed and one must select the best set of locations on which to open sites. Moreover, adapting a site in order to make it worth safely storing supplies takes time. This is also considered in our model.

The population is located in several non-overlapping zones and the amount of supplies distributed for each zone impacts the survival rate. Our problem is to select the distribution centers and the daily distributions in order to maximize the survival rate of the population. The survival rate is a non-linear function and thus our resulting model is non-linear.

3.1 Mathematical Formulation

The mathematical model we propose couples the humanitarian aid distribution with an approximation of the survivability rate. People which receive aid are more likely to survive a post-disaster situation, hence we are looking for the distribution with the highest impact. Each supply unit is meant for covering the need for an individual over one period of time. The model is built on the assumption of a fair distribution over a group of persons, that is the number of units is fairly spread over the group. Thus the group acts as a homogeneous entity. Consequently, the survivability rate is considered for the population and it is improved with a better distribution of supplies. Besides, the survivability rate is parameterized on the daily needs covering. As a consequence, given a population size p and a delivery d over the time period, the survivability rate τ is defined as a non-linear function $f()$ of the daily covered needs:

$$\tau = f(d/p) \tag{1}$$

The model relies on two components: (i) facility location to chose the location and opening time and (ii) distribution planning to deliver aid to the population. An initial inventory is supposed to be available after the disaster, at the beginning of the humanitarian operations, and the model is indexed over the time periods. Only immediate help is considered, which does not taken into account waste cleaning, buildings consolidation or reconstruction or durable population relocation into safer areas.

Let T be the number of time periods for the immediate humanitarian operations. It corresponds to the interval time, considered here in days, needed to provide the immediate humanitarian aid. Let Q be the total amount of available supplies (e.g. food, water, bandages and drugs), H be the available logistics human resources (e.g. personals and materials to operate the network distribution system) and C be the available budget. Furthermore, I and J are respectively the set of zones to be attended and the potential sites to set a distribution center (store and distribute supplies). For each potential site $j \in J$, let H_j and Q_j be respectively the number of human resources needed to open and operate it, and its distribution capacity. The cost for operating a distribution site j and the unit distribution cost from site j to zone i are respectively denoted C_j and C_{ij}. The initial population size for the zone i is defined as P_i.

Variables p_i^t determine the population for zone i at time t. The distribution is given by variables x_{ij}^t, which tells the amount of supplies provided by site i to zone i, at the time t. Variables y_i specify the date the site i is opened.

A mathematical formulation is provided from (2) to (16), where the objective is to maximizing the final population, considering all zones and times.

$$z = \max \sum_{i \in I} p_i^T \tag{2}$$

$$\sum_{j \in J} \sum_{t=1 \dots T} H_j (T - y_j) \leq H \tag{3}$$

$$\sum_{i \in I} x_{ij}^t \leq Q_j \quad \forall j \in J, \forall t = 1 \dots T \tag{4}$$

$$\sum_{t=1 \dots T} \sum_{j \in J} \sum_{i \in I} x_{ij}^t \leq Q \tag{5}$$

$$\sum_{j \in J} \left(C_j u_j + \sum_{t=1 \dots T} \sum_{i \in I} C_{ij} w_{ij}^t \right) \leq C \tag{6}$$

$$T \cdot u_j \geq y_j \quad \forall j \in J \tag{7}$$

$$Q_j \cdot w_{ij}^t \geq x_{ij}^t \quad \forall i \in I, \forall j \in J, \forall t = 1 \dots T \tag{8}$$

$$p_i^0 = P_i \quad \forall i \in I \tag{9}$$

$$p_i^{t+1} = p_i^t \cdot f\left(\frac{\sum_{i \in I} x_{ij}^t}{p_i^t}\right) \quad \forall i \in I, \forall t = 1 \dots T-1 \tag{10}$$

$$y_j \leq T \quad \forall j \in J \tag{11}$$

$$p_i^t \geq 0 \quad \forall i \in I, \forall t = 1 \dots T \tag{12}$$

$$x_{ij}^t \geq 0 \quad \forall i \in I, \forall j \in J, \forall t = 1 \dots T \tag{13}$$

$$y_j \in \mathbb{N} \quad \forall j \in J \tag{14}$$

$$u_j \in \{0,1\} \quad \forall j \in J \tag{15}$$

$$w_{ij}^t \in \{0,1\} \quad \forall i \in I, \forall j \in J, \forall t = 1 \dots T \tag{16}$$

The objective function (2) aims at maximizing the population size at the end of the time period. Inequalities (3) guarantee the human resources to be deployed to all open distribution centers at each time period do not exceed H. Restrictions (4) and (5) state the limits of supplies that can be distributed. Constraints (4) determine the distribution capacity for each center j at each period of time. Inequality (5) limits the total amount of supplies available for distribution. Constraint (6) sets the global financial limit. Since y_j are integer and x_{ij}^t are continuous, auxiliary binary variables u_j and w_{ij}^t, defined in (7) and (8), have been introduced to properly add the corresponding cost in (6). Variable u_j tells if center j is open, and w_{ij}^t tells if there is distribution from center j to zone i on time t.

The initial population size in each area is set in Equations (9). Equations (10) set the population evolution in each area at each period of time. The variables definition are provided in (12) to (16).

This problem is NP-hard as it generalizes the location problem. Moreover, it is non-linear due to the functions f. Thus, solving it exactly might require a too large time, even on small instances, in a context of crisis logistics.

4 HEURISTIC STRATEGIES

We propose a decomposition-based heuristic to compute solutions of good quality. The master level consists in choosing which site to open and at which period of time. The slave level computes a supplies distribution in order to maximize the final population, given opening dates for the sites (see Figure 3). Thus, the master level retains most of the combinatorial complexity of the problem while the slave problem deals with the complexity of the population dynamics. The later should ideally be tackled by simulation.

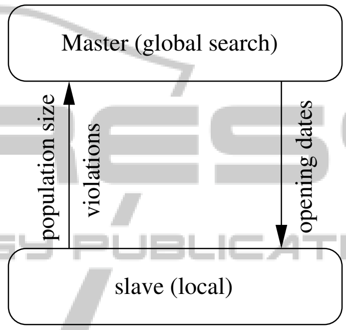

Figure 3: The master-slave organization.

In this decomposition, the master problem is in charge of finding the best combination of opening dates for the potential sites by setting the y vector. The slave subproblem receives the y vector from the master and computes the best distribution schedule (x variables) in order to optimize the population size z at the end of the considered period of intervention. Then, it returns the best value z found, given y.

This mathematical decomposition is considered as a black-box optimization system. NOMAD solver (Le Digabel, 2011) is used to compute the y vector. The slave subproblem is treated as a black-box which provides evaluation and violations measures given input values set by NOMAD. The evaluation corresponds to the value z and the violations refer to structural constraints (3) and (6). Indeed, the solver cannot handle explicitly constraints on the y vector and unfeasible vectors may be submitted to the slave.

The subproblem is solved by a local search. Its first step consists in checking the violations of the human and financial resources constraints. If y is unfeasible, an infinite value and the violations are returned. Otherwise, an initial distribution is computed by a constructive heuristic and the solution is improved by a local search procedure (see Figure 4).

The constructive heuristic H_1 works by first setting each site availability according to y. The financial resources are updated accordingly. Then, for

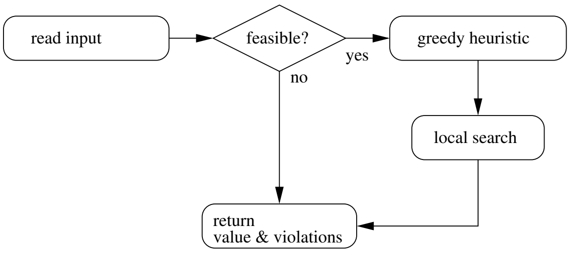

Figure 4: The algorithmic scheme of the black-box.

each time period, the supplies are assigned to the open sites, respecting their capacities and the available stock of supplies. The distribution is performed for each site. The zones are sorted on their distance to the site and the distribution starts with the closest one. Once the need for a zone is fulfilled, the next next zone is considered, until the supplies are all distributed or all the zones are covered. Since H_1 relies on a greedy approach for distributing the supplies, it can run short of supplies at the last periods of time. Thus another heuristic, H_2, is proposed. It tries to define a more balanced distribution by first computing the total distribution capacity for the sites open. Then the supplies are assigned to each site and each period of time, using the ratio of the capacity over the total capacity. The way the supplies are distributed to the zones is similar to H_1.

Three neighborhood structures, N_1, N_2 and N_3 are proposed to improve the distribution, while respecting the site availability and the financial constraint. Each kind of move addresses the distribution balance with respect to one dimension of the problem (the set of zones, the set of sites and the time periods), see Figure 5. A move from the structure N_1 considers one site and one zone. It looks for supplies transfer from one time period to another one in such a way the final population of the zone is improved. A move from the second neighborhood structure N_2 considers one site and one period of time. It tries to balance the supplies distribution by transferring supplies from a zone to another one in order to improve the total final population size of the two zones. A move from the third neighborhood structure N_3 considers one zone and one period of time. It aims at reducing the distribution cost by transferring supplies from one site to another one. Such a move does not have any impact on the population since the amount of delivered supplies does not change. However, by reducing the cost, the objective is to allow moves from N_1 and N_2 that were previously forbidden due to the financial limitation.

Those moves are used in a Variable Neighborhood Descend (VND) local search. This method has been proposed by (Mladenovic and Hansen, 1997) and it is

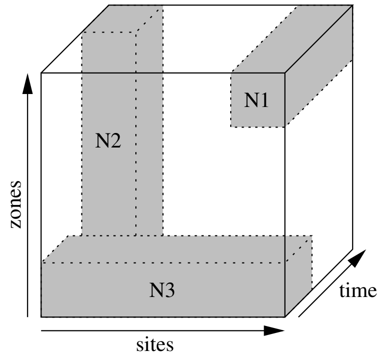

Figure 5: The impact of each neighborhood.

well-suited to the use of several neighborhood structures. The structures are first sorted according to their complexity, *i.e.* $N_1/N_2/N_3$. Only one structure is active each iteration. The method starts with the initial solution s_0 and the first neighborhood structure, that is N_1. Given an iteration, let k be the index of the active structure and s the current solution. If an improving solution s' is found, it becomes the new current solution ($s \leftarrow s'$) and $k \leftarrow 1$. Otherwise the current solution does not change and $k \leftarrow k+1$. The VND stops when $k > 3$, *i.e.* when both three structures have failed identifying an improving solution. Thus the current solution is a local optima with respect to the three neighborhood structures.

5 COMPUTATION RESULTS

The experiments were carried out on an Intel Xeon CPU at 2.27GHz, with 8 cores, 8MB of cache, 16GB of RAM, and using the operating system Ubuntu version 10.04. The algorithms were implemented in C++ using the GCC version 4.6.3. The solver NOMAD has been set to perform up to 500 evaluations and the initial solution given to NOMAD is set with all sites closed.

Several experiments have been performed over a set of simulated scenarios and one real scenario from the city of Belo Horizonte in Brazil. These instances are described in the sequence (Section 5.1). The first set of experiments aims at evaluating the impact of the heuristics and the local searches under the considered scenarios (Section 5.2). The second set is dedicated to measuring the quality of the overall framework, including the NOMAD solver (Section 5.3).

5.1 Test Scenarios

Let a scenario be a set of parameters which corresponds to a post-disaster situation. Some simplifications have been used in order to better evaluate the impact of the proposed methods. Two majors set of scenarios are considered in the computational experiments.

The first and the second set of scenarios contains the fixed parameters given in Table 1.

Table 1: Parameters statements for the first and the second sets of scenarios.

First scenario	
Parameters	Values
Number of time periods	8 days
Number of zones	10 zones
Number of sites	**varies from 2 to 12 sites**
Size of the population	100,000 people
Supplies for distribution	6 days
Budget	Unlimited
Human resources	Unlimited

Second scenario	
Parameters	Values
Number of time periods	8 days
Number of zones	10 zones
Number of sites	10 sites
Size of the population	100,000 people
Supplies for distribution	**varies from 1 to 8 days**
Budget	Unlimited
Human resources	Unlimited

For the sake of clarity, the parameter supply for distribution means that the variable resources cover a number of days. Using those characteristics for the first scenario, experiments have been designed varying the number of sites from 2 to 12. Considering the second set of scenarios, the variability is set on the amount of available supplies to be distributed which ranges from 1 to 8 days.

The real scenario uses data from Belo Horizonte. The main 9 urban zones are considered, with their population, as shown in Table 2

Table 2: Population size for Belo Horizonte (2012).

zone	population
Barreiro	282,552
Centro-sul	283,776
Leste	238,539
Nordeste	290,353
Noroeste	268,038
Norte	212,055
Oeste	308,549
Pampulha	226,110
Venda nova	265,179
Total	2,375,151

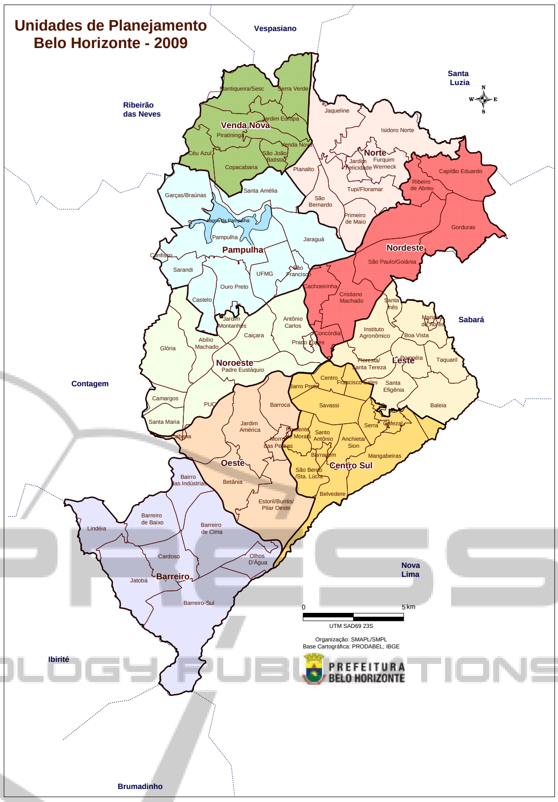

Figure 6: The 9 zones of Belo Horizonte.

5.2 First Set of Experiments

Figures 7 and 8 illustrate the impact of the proposed greedy heuristics (H_1 and H_2) and the three neighborhoods (N_1, N_2 and N_3) on the final population.

Results in Figure 7 show that when the number of sites increases, the greedy heuristic H_1 has a worst performance than the heuristic H_2. But the local search is able to achieve the same level of solution quality. In addition, when there are more sites available as for 10 and 12, the heuristic H_1 consumes the total amount of supplies in the first time periods. As consequence, the neighborhood N_1 has a higher impact since it works on the time period.

Figure 7 shows that, as the number of sites increase, the number of people assisted gets higher, until it reaches a maximum, on instances with 8, 10 or 12 sites. This happens because on the first 3 instances, the capacity of the sites are bottlenecks to the distribution. Furthermore, the greedy heuristic H_1 has a worse performance on the last instances. With more sites, H_1 tends to spend all material resources on the beginning, and lack supplies to use on the final time periods. Nevertheless, after the local search, the solutions obtained are similar, meaning that the search is robust enough to cope with different initial solutions.

The same behavior is seen on Figure 8. It presents a clear increase on the quality of the solution, as the amount of food available increases. On the last instance, when there is food enough for all days, the greedy heuristics are capable of distributing the food efficiently. Figure 11 and Figure 12 corroborate with the analysis made for Figure 7 and Figure 8.

In terms on execution times, both Figures 9 and Figure 10 show that neighborhoods N_1 and N_2 are responsible for most of the time consumption. This can be explained by the computational complexity of the operations. The greedy heuristics is $O(n^4 logn)$, while the local search is $O(n^6)$. The neighborhood N_3 does not take as long as N_1 and N_2 because, since it does not affect the population directly, there is no need to recompute the population after a move, meaning that it can be evaluated in $O(n^4)$, opposed to N_1 and N_2 that take $O(n^6)$ operations.

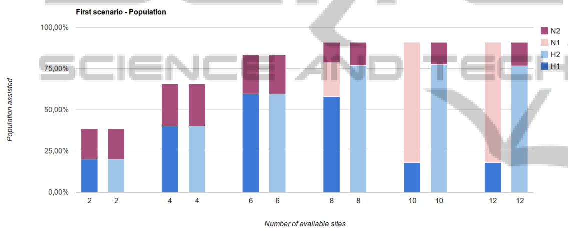

Figure 7: The impact on the population considering the first scenario.

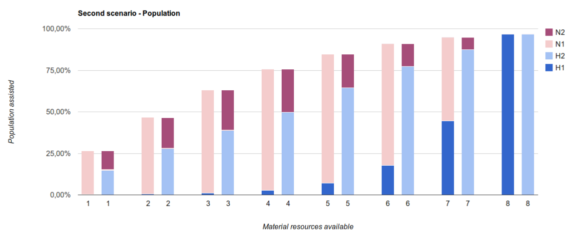

Figure 8: The impact on the population considering the second scenario.

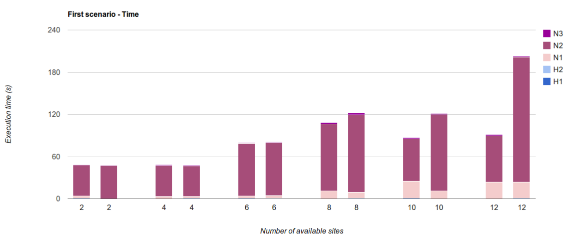

Figure 9: The impact of the proposed heuristics on the running time for the first scenario.

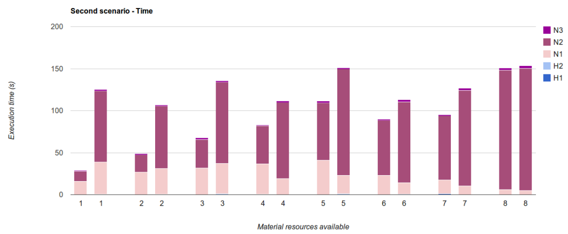

Figure 10: The impact of the proposed heuristics on the running time for the second scenario.

5.3 Second Set of Experiments

For the realistic instance (Tables 11 and 12), H_1 still produces worse results than H_2. Neighborhood structure N_1 helps reaching the same quality as H_2. After the VND, solutions from both heuristics have the same level of performance.

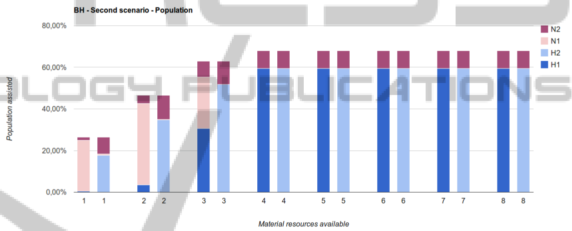

Figure 11: The impact on BH instance considering the first scenario.

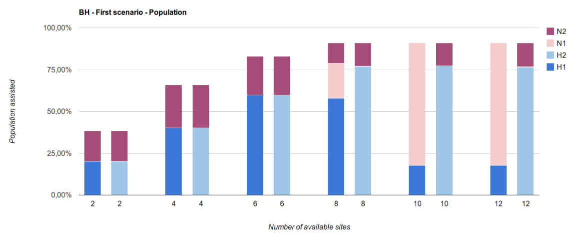

Figure 12: The impact on BH instance considering the second scenario.

6 CONCLUSIONS

We have considered the problem of setting a supplies distribution system in a post-disaster context. The primary decision variables correspond to the site opening schedule and the secondary variables focus on the supplies distribution to the population zones. The objective is to optimize the supply delivery to the population, while satisfying some logistics restrictions. We have proposed a decomposition in which the master level is addressed by NOMAD solver. The slave is considered as a black-box and it consists of two heuristics and a VND local search. Numerical results on both random instances and one realistic instance, using several scenarios, shows our approach provides satisfactory results. Besides, the overall response time is kept limited since NOMAD is able to work with very few calls to the black-box. We are currently investigating several extensions in order to deal with more realistic population evolution dynamics.

REFERENCES

Abounacer, R., Rekik, M., and Renaud, J. (2014). An exact solution approach for multi-objective location-transportation problem for disaster response. *Computers & Operations Research*, 41:83–93.

Afsar, H. M., Prins, C., and Santos, A. C. (2012). Exact and heuristics strategies for solving the generalized vehicle routing problem. In *Proceedings of the 5th International Workshop on Freight Transportation and Logistics*, ODYSSEUS, pages 91–94, Mykonos, Greece.

Afsar, H. M., Prins, C., and Santos, A. C. (2014). Exact and heuristic algorithms for solving the generalized vehicle routing problem with flexible fleet size. *International Transactions in Operational Research*, 21(1):153–175.

Berkoune, D., Renaud, J., Rekik, M., and Ruiz, A. (2012). Transportation in disaster response operations. *Socio-Economic Planning Sciences*, 46:23–32.

Boin, A. and McConnell, A. (2007). Preparing for critical infrastructure breakdowns: the limits of crisis management and the need for resilience. *Journal of Contingencies and Crisis Management*, 15(1):50–59.

Bruneau, M., Eeri, A. M., Chang, S. E., Eeri, B. M., T, R., Eeri, C. M., Lee, G. C., Eeri, A. M., Orourke, T. D., Eeri, D. M., Reinhorn, A. M., Eeri, E. M., Shinozuka, M., Kathleen, F., Eeri, G. M., Wallace, W. A., and I, D. V. W. (2003). A framework to quantitatively assess and enhance the seismic resilience of communities. *Earthquake Spectra*, 19:733–752.

Bruneau, M. and Reinhorn, A. (2007). Exploring the concept of seismic resilience for acute care facilities. *Earthquake Spectra*, 23(1):41–62.

Haimes, Y. Y. (2009). On the definition of resilience in systems. *Risk Analysis*, 29(4):498–501.

Le Digabel, S. (2011). Algorithm 909: NOMAD:nonlinear optimization with the MADS algorithm. *ACM Transactions on Mathematical Software*, 37(4):1–15.

Liberatore, F., Ortuo, M., Tirado, G., Vitoriano, B., and Scaparra, M. (2014). A hierarchical compromise model for the joint optimization of recovery operations and distribution of emergency goods in humanitarian logistics. *Computers & Operations Research*, 42(0):3 – 13.

Mezzou, O., Birregah, B., and Châtelet, E. (2011). A theoretical study of the interactions between the components of resilience in critical urban infrastructures. In *Smart and Sustainable City (ICSSC 2011), IET International Conference on*, pages 1–6.

Mladenovic, N. and Hansen, P. (1997). Variable neighborhood search. *Computers & Operations Research*, 24(11):1097–1100.

Nolz, P. C., Doerner, K. F., Gutjahr, W. J., and Hartl, R. F. (2010). A bi-objective metaheuristic for disaster relief operation planning. In Coello, C. A. C., Dhaenens, C., and Jourdan, L., editors, *Advances in Multi-Objective Nature Inspired Computing*, volume 272 of *Studies in Computational Intelligence*, pages 167–187. Springer.

Prins, C., Santos, A. C., and Afsar, H. M. (2012). Splitting procedure and a relaxed iterated local search for the generalized vehicle routing problem. In *Procedings of the Latino-Iberoamericano de Investigación Operativa, Simpósio Brasileiro de Pesquisa Operacional*, CLAIO-SBPO, Rio de Janeiro, Brazil.

Rath, S. and Gutjahr, W. J. (2014). A math-heuristic for the warehouse locationrouting problem in disaster relief. *Computers & Operations Research*, 42:25–39.

Rottkemper, B., Fischer, K., and Blecken, A. (2012). A transshipment model for distribution and inventory relocation under uncertainty in humanitarian operations. *Socio-Economic Planning Sciences*, 46:98–109.

Vitoriano, B. n., Ortuño, M., Tirado, G., and Montero, J. (2011). A multi-criteria optimization model for humanitarian aid distribution. *Journal of Global Optimization*, 51(2):189–208.