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Transportation Research Procedia 30 (2018) 304–313

Transportation Research Procedia

www.elsevier.com/locate/procedia

EURO Mini Conference on "Advances in Freight Transportation and Logistics" (emc-ftl-2018)

A fast heuristic for routing in post-disaster humanitarian relief logistics

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Abstract

In the last decades, natural disasters have been affecting the human life of millions of people. The impressive scale of these disasters has pointed out the need for an effective management of the relief supply operations. One of the crucial issues in this context is the routing of vehicles carrying critical supplies and help to disaster victims. This problem poses unique logistics challenges, including damaged transportation infrastructure and limited knowledge on the road travel times. In such circumstances, selecting more reliable paths could help the rescue team to provide fast services to those in needs. The classic cost-minimizing routing problems do not properly reflect the relevant issue of the arrival time, which clearly has a serious impact on the survival rate of the affected community. In this paper, we focus specifically on the arrival time objective function in a multi-vehicle routing problem where stochastic travel times are taken into account. The considered problem should be solved promptly in the aftermath of a disaster, hence we propose a fast heuristic that could be applied to solve the problem.

Keywords: : Humanitarian relief routing; Uncertain travel time; Mean-risk model; Heuristic

1. Introduction

Throughout the world, many countries have faced a series of unpredictable natural disasters such as the earthquake in Japan, the Southeast Asian floods in 2011, the Hurricane Irma in the United States in 2017, to mention a few. These

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10.1016/j.trpro.2018.09.033

disasters caused thousand deaths and affected millions of people with substantial social and environmental damages. Humanitarian logistic operations play a critical role in minimizing loss of lives and alleviating human suffering after disasters by providing relief supplies such as water, food and medical services. These logistic activities should be effective and efficient to provide timely response and quick recovery activities after a catastrophe. Given the lack of precise information regarding the affected population, the limitations in transportation resources and the damaged infrastructure, it is challenging to plan these operations very carefully. Considering the uncertain features of disaster relief operations, and in particular, the realistic scenario that a disaster can damage the roads of the relief regions, we propose, in this paper, a fast heuristic for the post-disaster relief routing under uncertain travel times.

Our problem can be classified as a selective multi-vehicle cumulative routing problem with stochastic travel times. While vehicle routing problems are generally a very well-researched class of decision problems, the contributions into the class of cumulative vehicle routing problems are scarce and rarely applied to actual real-world settings. Research efforts have been devoted to design efficient metaheuristic methods for solving the problem and its variants. Salehipour et al. (2011) and Silva et al. (2012) proposed heuristic approaches for the single vehicle problem. In (Mladenovic et al., 2013), the authors presented a general variable neighborhood search metaheuristic for the traveling deliveryman problem. Ngueveu et al. (2012) presented a memetic heuristic for the cumulative capacitated vehicle routing problem aimed at visiting a set of customers with a homogenous capacitated vehicle fleet. Ribeiro and Laporte (2012) presented an adaptive large neighborhood metaheuristic for the capacitated problem, applying different repair and destroy procedures. In a recent paper, Sze et al. (2017) proposed a hybrid metaheuristic algorithm in which a two-stage adaptive variable neighborhood search algorithm is proposed. More recently, an efficient new formulation, defined on a multi-level network has been presented in (Nucamendi-Guillén et al., 2016), for the deterministic k-traveling repairman problem without profits enhanced by a metaheuristic approach.

The literature on the selective variant (also named in the literature as the traveling repairman problem with profits) is relatively scarce, even in the deterministic case, for which Dewilde et al. (2013) first presented an integer linear programming formulation in which the number of visited nodes, or equivalently the path length, is an input parameter. When uncertainty is considered, the literature on the traveling repairman problem is completely absent, whilst the literature on other vehicle routing problems with stochastic components is quite rich (Oyola et al., 2017). The two major approaches proposed to deal with this more involved case are represented by the Stochastic Programming (Beraldi et al., 2017b, Perboli et al., 2017) and the Robust Optimization paradigms (Bruni et al., 2014). The former can be applied when uncertainty can be described by known distributions, whereas the latter is preferred when only partial information is available. Restricting the attention to uncertainty in travel times, we mention the risk-based model proposed in (Lecluyse et al., 2009), for a time-dependent routing problem, the probabilistic chance-constraint model for a capacitated time-dependent vehicle routing proposed by Nahum and Hadas (2009) and the vehicle routing problem with time-dependent and stochastic travel times studied by Taş¸ et al. (2014). A model for minimizing the total costs incorporating the uncertainty of link travel times with the early arrival and delay penalty at customers who set up designated time windows has been presented in (Ando and Taniguchi, 2006), whereas Musolino et al. (2016) presented a procedure for the solution of the vehicle routing problem based on reliable link travel times. This paper deals with the challenging task of estimating travel times on a road network by taking into account spatially aggregated traffic conditions estimated by means of a network fundamental diagram (Musolino et al., 2014; Musolino and Vitetta, 2014), as well as disaggregated data concerning the congested link travel times. The model is then solved by using a genetic algorithm (Polimeni and Vitetta, 2014).

Even though in the last decade, the scientific community has devoted an increasing attention on the application of operations research techniques for the emergency and post-disaster management (Aringhieri et al., 2017; Khodaparasti et al., 2016; Hoyos et al., 2015; Huang et al., 2012), only a few papers address relief routing decisions, and among them, only (Ahmadi et al., 2015) incorporates the stochasticity of travel times by means of scenarios. The model, by adopting a risk neutral approach, aims at determining the locations of local shelters and routing for last mile distribution after an earthquake. Pourrahmani et al. (2015) presented a routing model for relief evacuation after earthquake in which the variations of travel times over different time intervals is handled using a multi-period routing model and the number of evacuees is a fuzzy number. In (Shahparvari et al., 2017), the authors addressed the case in which the shelter and the vehicle capacity as well as the evacuation time window are fuzzy numbers. In another paper, they considered the case in which the randomness of the uncertain parameters are handled by robust programming and presented a stochastic robust model, then solved by a genetic algorithm (Shahparvari and Abbasi, 2017). We should mention that evacuation is the process of transferring people from affected areas or local shelters to open spaces equipped with emergency facilities (such as supplies of electricity, water and sanitary facilities). Hence, evacuation problem can not be directly cast into our problem, which seeks instead routes from a central depot to different affected areas.

It is interesting to note that, still many studies in disaster response context, even those we mentioned, promote cost-based functions expressed as the total traveled time or the total unmet demands. It is worthwhile remarking that the biggest difference between routing in post-disaster and other kinds of routing problems is that the arrival time at victims' locations, rather than the total travel time, is the most important objective function. This paper contributes to the relief routing literature by recognizing the customer-centric nature of the problem focusing on the arrival time of a fleet of vehicles to the areas affected by the disaster. Moreover, since in different locations a different number of disaster victims may be found, we consider a utility of servicing each location, as a proxy of the number of people in need. Hence, the affected areas are prioritized according to the utility level, that is proportional to the disaster severity and the population size. The goal is to find the optimal plan to service a subset of the affected areas, with a limited fleet of vehicles. We mention that Balcik (2017) very recently proposed an efficient tabu search heuristic for solving a problem for post-disaster needs assessment that involves site selection decisions in addition to the routing decisions. This paper is closely related to our approach, but it shows also significant differences. First of all, the objective function is different, since in (Balcik, 2017) the maximum coverage ratio is minimized. It is well-recognized that considering the arrival time as an objective function in routing problems poses severe computational issue, even in the deterministic case. Secondly, the mentioned paper does not consider uncertainty in travel times. Moreover, in this paper, we address risk-averse route decisions in the aftermath of a disaster, considering different risk attitudes of the decision maker. The remainder of the paper is organized as follows.

In Section 2, we introduce the problem. The heuristic framework is presented in Section 3. Section 4 is devoted to the computational results obtained by implementing the proposed heuristic on a set of instances, and concluding remarks are discussed in Section 5.

2. Problem definition

Let us consider an affected area and a pre-specified central depot (denoted with 0). Potential victims after a disaster are assumed to be concentrated into some demand points $i \in \mathcal{N}$. A limited fleet of V vehicles with unlimited capacity is available to serve the locations. A feasible solution consists of a set of disjoint paths $\pi^v = [0, l_{[1]}, \dots, l_{[L^v]}], v = 1, \dots, V$ defined by an ordered set of links indexed by l (here L^v denotes the length of path v). The notation $[\cdot]$ denotes the position of the link in the path. We denote by $\pi_i^v \subseteq \pi^v$ the subpath connecting the depot to the node i and by $\mathcal{N}^v$, the set of nodes visited by the vehicle v, which are the endpoints of the links $l \in \pi^v$.

The objective is to identify a set of feasible vehicle paths (each visiting a different subset of nodes) that maximizes the utility of relief distribution amongst beneficiaries. Utility is expressed as a decreasing function of the arrival times and it assumes the maximum value (the absolute utility score p_i) when the arrival time at node i (t_i) is zero. If we express at each node i the utility as $p_i - t_i$, the total utility function $\mathcal{UF}$ associated to a given solution (set of vehicle paths) $R = [\pi^v]_{v=1}^V$ is then

$$\mathcal{UF}(R) = \sum_{v=1}^{V} \sum_{i \in \mathcal{N}^v} (p_i - t_i).$$

Since transport infrastructures in affected areas might be partially damaged, each road may experience a given travel time variability. The travel time d_l of each edge l of the network is represented by a random variable with mean $E(\tilde{d}_l)$ and variance $VAR(\tilde{d}_l)$. We assume, in this paper for ease of exposition, that the travel times are independent, which might be not the case, especially in emergency situations. We should mention that, even though the following derivation is presented for the uncorrelated case, the approach proposed is general and can be applied also when the travel times are dependent. As a consequence, the arrival time of the server at node i is itself a random variable (denoted with $\tilde{t}_i$). We incorporate a risk measure in our problem, by combining the mean travel time with some measure of the dispersion. The standard deviation is a very intuitive measure of variability, which is also related to the value-at-risk objective (Beraldi et al., 2012, 2017a, 2018) and that can be used whenever the first and the second moments of the distribution function of the travel times are known (Beraldi et al., 2015). The mean-risk function associated to a set of paths R under uncertain travel times is then

$$\mathcal{UF}(R) = \lambda E[\sum_{v=1}^{V} \sum_{i\in\mathcal{N}^v} (p_i - \tilde{t}_i)] + (1-\lambda)\sqrt{\mathrm{VAR}[\sum_{v=1}^{V} \sum_{i\in\mathcal{N}^v} (p_i - \tilde{t}_i)]}$$

where the parameter $\lambda \in (0,1)$ plays the role of the trade-off weight in mean-risk models (Lecluyse et al., 2009). By decreasing its value more weight is put on the non-linear part of the objective function, reflecting a risk-averse behavior of the decision maker. We note that $\tilde{t}_{i+1}$ depends on $\tilde{t}_i$ since we can rewrite $\tilde{t}_{i+1} = \tilde{t}_i + \tilde{d}_{(i,i+1)}$. Hence, in evaluating the variance of the utility function we should also account for the covariance term between the arrival times at two generic nodes $i, j \in \mathcal{N}^v$. Note that, even though the arrival times are dependent, it turns out that the total variance can be computed independently for each vehicle as the paths cover disjoint subsets of nodes. In particular,

$$\mathrm{VAR}\left[\sum_{v=1}^{V}\sum_{i\in\mathcal{N}^v}(p_i - \tilde{t}_i)\right] = \sum_{v=1}^{V}\mathrm{VAR}\left[\sum_{i\in\mathcal{N}^v}\tilde{t}_i\right] = \sum_{v=1}^{V}\left(\sum_{i\in\mathcal{N}^v} VAR(\tilde{t}_i) + \sum_{i\in\mathcal{N}^v}\sum_{\substack{j\in\mathcal{N}^v\\ i\neq j}} COV(\tilde{t}_i,\tilde{t}_j)\right).$$

The arrival time at each node is the sum of the travel times associated to the links $l \in \pi_i^v$ i.e. belonging to the subpath connecting the depot to the node i. Hence,

$$E(\tilde{t}_i) = E\left[\sum_{l\in\pi_i^v}\tilde{d}_l\right] = \sum_{l\in\pi_i^v} E(\tilde{d}_l) \text{ and } VAR(\tilde{t}_i) = VAR\left(\sum_{l\in\pi_i^v}\tilde{d}_l\right) = \sum_{l\in\pi_i^v} VAR(\tilde{d}_l).$$

The covariance between t_i and t_j can be be evaluated as follows:

$$COV(\tilde{t}_i,\tilde{t}_j) = E[\tilde{t}_i\tilde{t}_j] - E[\tilde{t}_i]E[\tilde{t}_j] = E\left[\sum_{l\in\pi_i^v}\tilde{d}_l \times \sum_{l'\in\pi_j^v}\tilde{d}_{l'}\right] - E\left[\sum_{l\in\pi_i^v}\tilde{d}_l\right]E\left[\sum_{l'\in\pi_j^v}\tilde{d}_{l'}\right] =$$

$$= E\left[\sum_{l\in\pi_i^v\cap\pi_j^v}\tilde{d}_l^2 + \sum_{l\in\pi_i^v,\notin\pi_j^v}\sum_{l'\in\pi_j^v,\notin\pi_i^v}\tilde{d}_l\tilde{d}_{l'}\right] - \left[\sum_{l\in\pi_i^v}E(\tilde{d}_l)\right]\left[\sum_{l'\in\pi_j^v}E(\tilde{d}_{l'})\right] =$$

$$= E\left[\sum_{l\in\pi_i^v\cap\pi_j^v}\tilde{d}_l^2\right] + E\left[\sum_{l\in\pi_i^v,\notin\pi_j^v}\sum_{l'\in\pi_j^v,\notin\pi_i^v}\tilde{d}_l\tilde{d}_{l'}\right] - \sum_{l\in\pi_i^v\cap\pi_j^v}E^2(\tilde{d}_l) - \sum_{l\in\pi_i^v,\notin\pi_j^v}\sum_{l'\in\pi_j^v,\notin\pi_i^v}E(\tilde{d}_l)\mathrm{I}E(\tilde{d}_{l'}) =$$

$$= \sum_{l\in\pi_i^v\cap\pi_j^v}E(\tilde{d}_l^2) - \sum_{l\in\pi_i^v\cap\pi_j^v}E^2(\tilde{d}_l) + \sum_{l\in\pi_i^v,\notin\pi_j^v}\sum_{l'\in\pi_j^v,\notin\pi_i^v}E(\tilde{d}_l\tilde{d}_{l'}) - \sum_{l\in\pi_i^v,\notin\pi_j^v}\sum_{l'\in\pi_j^v,\notin\pi_i^v}E(\tilde{d}_l)E(\tilde{d}_{l'}) =$$

$$= \sum_{l\in\pi_i^v\cap\pi_j^v}[E(\tilde{d}_l^2) - E^2(\tilde{d}_l)] + \sum_{l\in\pi_i^v,\notin\pi_j^v}\sum_{l'\in\pi_j^v,\notin\pi_i^v}[E(\tilde{d}_l\tilde{d}_{l'}) - \mathrm{I}E(\tilde{d}_l)E(\tilde{d}_{l'})] = \sum_{l\in\pi_i^v\cap\pi_j^v}VAR(\tilde{d}_l)$$

since the second term is the covariance between the links l and l' which is zero, for hypothesis.

Proposition

Let q be the position of the link $\ell \in \pi^v$ assuming value in the interval $[1, \dots, L^v]$. For each vehicle, $v \in V$

$$\mathrm{VAR}\left[\sum_{i\in\mathcal{N}^v}\tilde{t}_i\right] = \sum_{q=1}^{L^v}(L^v - q + 1)^2 VAR(\tilde{d}_{[q]}).$$

Proof

$$\mathrm{VAR}\left[\sum_{i\in\mathcal{N}^v}\tilde{t}_i\right] = \sum_{i\in\mathcal{N}^v}VAR(\tilde{t}_i) + \sum_{i\in\mathcal{N}^v}\sum_{j\in\mathcal{N}^v, i\neq j}COV(\tilde{t}_i,\tilde{t}_j) = \sum_{i\in\mathcal{N}^v}\sum_{l\in\pi_i^v}VAR(\tilde{d}_l) + \sum_{i\in\mathcal{N}^v}\sum_{j\in\mathcal{N}^v,i\neq j}\sum_{l\in\pi_i^v\cap\pi_j^v}VAR(\tilde{d}_l).$$

In the first term, we count $L^v - q + 1$ times the variance $VAR(\tilde{d}_{[q]})$ for each $q = 1, \dots L^v$.

As far as the second term is concerned, we observe that we count $VAR(\tilde{d}_l)$ a number of times equal to

$$2\binom{L^v - q + 1}{2} = \frac{(L^v - q + 1)!}{(L^v - q + 1 - 2)!\,2!}$$

since it is considered for each non ordered pair of nodes (i, j). But

$$\frac{(L^v - q + 1)!}{(L^v - q + 1 - 2)!\,2!} = \frac{(L^v - q + 1)(L^v - q + 1 - 1)(L^v - q + 1 - 2)!}{(L^v - q + 1 - 2)!\,2!} = \frac{(L^v - q + 1)(L^v - q)}{2}$$

Then

$$\mathrm{VAR}[\textstyle\sum_{i \in \mathcal{N}^v} \tilde{t}_i] = \sum_{q=1}^{L^v} VAR(\tilde{d}_{[q]}) \left[(L^v - q + 1) + 2\frac{(L^v - q + 1)(L^v - q)}{2}\right] =$$

$$= \textstyle\sum_{q=1}^{L^v} VAR(\tilde{d}_{[q]})[(L^v - q + 1) + (L^v - q + 1)(L^v - q)] =$$

$$= \textstyle\sum_{q=1}^{L^v} VAR(\tilde{d}_{[q]})[L^v - q + 1](1 + (L^v - q))] = \sum_{q=1}^{L^v} (L^v - q + 1)^2 VAR(\tilde{d}_l).$$

In the Appendix A, we report a mathematical formulation based on position-dependent variables.

3. The iterated greedy heuristic

The iterated greedy method alternates between constructive and destructive phases. The greedy constructive method builds a solution R^{curr} involving a subset S of the node set $\mathcal{N}$. Additionally, an adaptive local search phase is applied to R^{curr} and a new solution $\hat{R}$ is obtained. Then, during the destructive phase, a percentage of the nodes $(10\%|N|)$ are removed randomly from the current solution and put in temporary blacklist TBL. The list is emptied at the end of the successive iteration. Next, the constructive phase is applied on the set set $S \backslash TBL$ again to rebuild the solution. The method iterates this pattern until a given number of iteration It_{max} is reached. The best solution $R*$ and the best value of the $\mathcal{UF}(R*)$ are stored and returned at the end of the algorithm. The pseudocode of the iterated greedy heuristic proposed to solve the problem is presented in Algorithm 1.

Algorithm 1: Scheme of the heuristic

Initialization: $TBL \leftarrow \emptyset, S \leftarrow \mathcal{N}; R*, \hat{R}, R^{curr} \leftarrow null; \mathcal{UF}(.) \leftarrow null$
for $It = 1$ *to* It_{max} **do**
  $R^{curr} \leftarrow null$
  $R^{curr} \leftarrow$ **Construction Procedure**(S)
  $\hat{R} \leftarrow$ **Adaptive local search**(R^{curr})
  if $\mathcal{UF}(\hat{R}) > \mathcal{UF}(R*)$ **then**
    $R* \leftarrow \hat{R}$
    $\mathcal{UF}(R*) \leftarrow \mathcal{UF}(\hat{R})$
  end
  Destroy procedure(S)
  $TBL \leftarrow \emptyset$
  while $it \leq 10\%|\mathcal{N}|$ **do**
    Select randomly a node $n \in S$
    $TBL \leftarrow TBL \bigcup \{n\}$
    $S \leftarrow S \setminus \{n\}$
    $it++$
  end
end
return $R*$

In the following, we discuss the main steps of the proposed heuristic in more detail. During the constructive phase, the **Construction Procedure** is called to build an initial solution. Nodes $\boldsymbol{i} \in \boldsymbol{S}$ are sorted in ascending order with respect to the following criterion

$$\frac{\boldsymbol{\lambda E(\tilde{d}_{(0,i)}) + (1 - \lambda)\sqrt{VAR(\tilde{d}_{(0,i)})}}}{\boldsymbol{\lambda\, p_i}}$$

which accounts for both the distance from the depot and the utility. One seed node is then inserted into each vehicle route, following a greedy ordering criterion (Guerriero et al., 2013). Then, each unvisited node is inserted one at a time, in the best position in the best route (on the basis of the increment of the utility value). There are many different alternatives that can be considered for the local search. Among them, we opted for a self-adaptive mechanism implemented in the **Adaptive local search** procedure. The idea is to randomly select one neighborhood in the set of neighborhoods $\{\mathbf{1}, \dots, \boldsymbol{K}\}$, accordingly to the associated selection probability. The set of neighborhoods $\{\mathbf{1}, \dots, \boldsymbol{K}\}$ is the following;

1. Intra-route exchange operation: exchanges the position of a pair of non-adjacent nodes over a path.

2. $2-$opt operation: deletes two non-adjacent edges along the path and add two other edges such that the direction of middle unchanged edges in the new path are reversed.

3. Or$-$opt operation: deletes any triple of non-adjacent edges within the path and reconnects them by adding three new edges such that the order of middle unchanged edges over the path is preserved.

4. Inter-route exchange operation: exchanges a pair of nodes belonging to two different paths.

5. Delete-insert operation: deletes a node from a path and adds it to the other one.

Within the $warm-up$ period, a roulette wheel mechanism is applied to determine which neighborhood to explore. The selection probability is the same for all the neighborhoods and set to $1/K$. After the $warm-up$ period, the neighborhood selection is performed using the self-adaptive mechanism considering the success and the failure of the neighborhoods in the past. In particular, the selection probability of the neighborhoods is updated every N_a iterations using the following formula $p_k = \frac{\bar{s}_k}{\sum_{k=1}^{K} \bar{s}_k}$ where $\bar{s}_k = \frac{s_k}{s_k + f_k} + \varepsilon$.

Here, s_k and f_k count the number of times the neighborhood k was successful or unsuccessful, respectively, and ε is a small value added to provide all the neighborhoods (even the unsuccessful ones) with a chance. When the local search is not able to improve the solution within a given number of iterations it is stopped and the destruction phase is applied again. The proposed **Destroy procedure** generates a subset of randomly selected nodes in the current solution to be banned from being present in the solution of next iteration. This kind of diversification mechanism allows us to extensively search the solution space in order to find near-optimal solutions. A scheme of the local search heuristic is shown in Algorithm 2.

Algorithm 2: Adaptive local search

Input: The current solution R^{curr}
Initialization: $p_k = \frac{1}{K}, \forall k = 1, \dots K; \hat{R} \leftarrow null$
for $t = 1$ *to* T **do**
  if ($t >$ *Warm-up Period and* $t \mod N_a = 0$) **then**
    Update-Selection-Probability(k)
  end
  Select a Neighborhood $\hat{k}$ according to the probabilities $p_k, \forall k = 1, \dots K$
  Explore the Neighborhood $\hat{k}$ around R^{curr} and return a solution $\hat{R}$
  if *No improvements after a certain number of Iterations* **then**
    return $\hat{R}$
  end
end
return $\hat{R}$

4. Computational results

This section shows the performance of the proposed heuristic on different test cases. The code was implemented in C++ and the experiments performed on an Intel CoreTM i7 2.90 GHz, with 8.0 GB of RAM memory, running under Windows operating system. In order to have an idea of the quality of the solution obtained, the corresponding mathematical model (reported in Appendix A) was solved using SCIP. We have tested the heuristic on two sets of instances, including the $P-$instances and the $E-$instances used as benchmark in routing problems (Nucamendi-Guillén et al., 2016). The number of customers (vehicles) in the data sets vary from $15-75$ $(2-15)$ and $21-75$

$(3-14)$, respectively. The expected travel time over each link (i,j) is set to the Euclidean distance between node i and j and its variance is computed as $\left[(rE(\tilde{d}_{(i,j)}))^2\right]$, where r is a random number uniformly distributed in the interval $[0.1,0.32)$. In order to randomly generate utility values, we have used the following formula $p_i \sim U((l,u])$ where $l = \min_{i=1}^{n}\left(E(\tilde{d}_{(0,i)}) - \alpha\sqrt{VAR(\tilde{d}_{(0,i)})}\right)$ and $u = \frac{n}{2}\max_{i=1}^{n}\left(E(\tilde{d}_{(0,i)}) + \beta\sqrt{VAR(\tilde{d}_{(0,i)})}\right)$. Here α,β are deviation parameters within interval $[0,1]$ which are determined by the decision maker.

The number of iterations It_{max} and T have been set to 20 and 1200, respectively. The $warm-up\ period$ has been set to 100 iterations and the local search is stopped after experiencing 20 inner iterations without any improvement. Also, the trade-off parameter λ is taken from the set $\{0.1, 0.5, 0.9\}$ and the probabilities are updated every $N_a = 10$ iterations. Tables 1 and 2 summarize the obtained results.

Table 1: Results for the P −Instances

Instance	|N|	|V|	λ = 0.1			λ = 0.5			λ = 0.9		
			Iterated greedy		SCIP	Iterated greedy		SCIP	Iterated greedy		SCIP
			ΔTime	ΔGap	Opt	ΔTime	ΔGap	Opt	ΔTime	ΔGap	Opt
Pn16k8	15	5	0.56	0.09	0.00	1.01	0	0.00	1.02	0.12	0.00
Pn19k2	18	2	0.05	0.06	0.00	1.18	0	0.00	1.19	0	0.00
Pn20k2	19	2	0.05	1.13	0.00	0.75	2.61	0.00	1.43	0	0.00
Pn21k2	20	2	0.03	3.65	0.00	0.86	0.76	0.00	1.12	0.71	0.00
Pn22k2	21	2	0.79	3.09	0.00	0.81	0.27	0.00	1.43	2.01	0.00
Pn22k8	21	8	0.35	0.84	0.00	0.46	0	0.00	0.56	0.33	0.00
Pn23k8	22	8	0.74	1.25	0.00	0.92	0.33	0.00	1.16	0.15	0.00
Pn40k5	39	5	0.03	0.39	7.87	0.15	0.53	0.00	0.84	1.17	0.00
Pn44k5	44	5	0.06	1.27	5.35	0.06	1.28	0.56	0.59	1.17	0.00
Pn50k7	49	7	0.07	1.78	10.19	0.07	1.27	0.75	0.81	0.86	0.00
Pn50k8	49	8	0.06	1.04	9.49	0.40	0.93	0.00	1.13	1.32	0.00
Pn50k10	49	10	0.26	1.41	0.00	0.06	0.4	0.14	3.01	0.43	0.00
Pn51k10	50	10	0.06	0.75	2.15	1.91	0.48	0.00	1.66	0.32	0.00
Pn55k7	54	7	0.09	4.06	9.36	0.09	1.87	0.66	0.81	2.77	0.00
Pn55k8	54	8	0.08	2.94	10.03	0.09	2.17	0.53	1.02	1.62	0.00
Pn55k10	54	10	1.15	3.81	0.00	0.97	2.82	0.00	2.18	2	0.00
Pn55k15	54	15	0.02	2.82	7.82	1.32	2.47	0.00	1.25	2.15	0.00
Pn60k10	59	10	0.58	0.92	0.00	0.11	0.72	0.42	2.48	0.8	0.00
Pn65k10	64	10	0.13	0.74	8.02	0.15	1.94	0.45	0.65	1.34	0.00
Pn70k10	69	10	0.18	0.62	7.58	0.20	1.32	0.46	0.95	1.21	0.00
Pn76k4	75	4	0.60	–	∞	0.59	-56.23	58.49	0.58	-107.59	110.28
Pn76k5	75	5	0.51	–	∞	0.54	–	∞	0.54	–	∞
average			0.29	1.63	4.343	0.58	-1.62	2.97	1.20	-4.15	5.25

The performance of the heuristic has been evaluated by comparing the solution with the one obtained by SCIP within a time limit of one hour. Columns 1, 2, and 3 refer to the name of instances, the number of nodes and the number of vehicles, respectively. Then, for each value of λ the speed up (in percentage) in the solution time (evaluated as $\Delta Time = \frac{CPU_{heu}}{CPU_{SCIP}} * 100$) and the percentage gap of the heuristic solution with respect to the solution provided by SCIP (evaluated as $\Delta Gap = \frac{OF_{SCIP} - OF_{heu}}{OF_{SCIP}} * 100$) are reported together with the percentage optimality gap (Opt) of the SCIP solution. By looking at the results in Tables 1-2, we observe that the heuristic provides quite satisfying solutions with the average gap limited to 1.63% for the P −instances. Moreover, we observe that for the most challenging instances of $Pn76k4$ and $Pn76k5$, either SCIP could not provide any feasible solution (verified by Opt of ∞) or provided low quality feasible solutions compared with the heuristic solutions (verified by the negative ΔGap values). In terms of solution time, the average speed-up ($\Delta Time$) is around 0.29% for the most complex case with $\lambda = 0.1$. The decrease in the value of λ, reflects a risk-averse behavior of the decision maker and exacerbate the complexity of the problem, since more weight is put on the non-linear part of the objective function. In the case of the E −instances, the average gap is limited to 1.16% and SCIP was not able to find any feasible solution for the most challenging instance $En76k7$ with $\lambda = 0.1$, whereas for five out of eight remaining instances the heuristic outperformed SCIP in terms of solution quality (see column 5 of Table 2). In what follows we also discuss about other findings which are not directly reported in the Tables. For instance, the proposed heuristic provides satisfying solutions with an average gap (evaluated over all the λ values) limited to 0.83 for the E −instances and to -1.43% for the P −instances, respectively. In addition, the proposed heuristic outperforms SCIP in terms of solution time, which is less than 20 seconds and on average around 4 seconds, for the P −Instances. The average solution time for the E −instances is around 24 seconds with a maximum value of less than 59 seconds for the instance $En76k7$.

Table 2: Results for the E −Instances

	λ = 0.1			λ = 0.5			λ = 0.9		
Instance |N| |V|	Iterated greedy SCIP			Iterated greedy SCIP			Iterated greedy SCIP		
	$\Delta Time$	ΔGap	Opt	$\Delta Time$	ΔGap	Opt	$\Delta Time$	ΔGap	Opt
En22k4 21 4	2	4.03	0.00	4.44	0.45	0.00	4.32	2.49	0.00
En23k3 22 3	3.93	6.04	0.00	5.72	2.84	0.00	4.43	3.76	0.00
En30k3 29 3	0.07	-1.6	17.45	0.16	0.57	0.00	2.42	1.49	0.00
En33k4 32 4	0.1	-0.63	14.04	0.12	0.63	0.88	3.4	0.84	0.00
En51k5 50 5	0.38	-0.5	6.61	0.41	0.51	0.56	2.88	0.5	0.00
En76k7 75 7	1.63	–	∞	1.6	0	1.11	1.61	0.51	0.38
En76k8 75 8	1.46	-1.77	5.42	1.47	0	0.47	1.47	0.19	0.31
En76k10 75 10	1.31	-0.13	2.56	1.28	0.34	0.26	3.08	0.33	0.00
En76k14 75 14	0.97	0.21	1.64	0.99	0.07	0.18	1.05	0.31	0.00
average	1.32	0.71	5.96	1.8	0.6	0.38	2.74	1.16	0.08

5. Conclusions

This paper introduces an important routing problem in post-disaster management, in which uncertainty affects travel times. Moreover, it considers the risk in a routing context, where the arrival time variability may have a severe impact on the benefits of a post-disaster logistic activity.

To solve the problem, we have developed an iterated greedy heuristic, easy to implement and very effective. The results show that our heuristic is able to provide good solutions very quickly. Our heuristic is flexible, as it is applicable to various risk measures. As a future work, we can consider correlated travel times. This situation can be relevant, especially in disaster management applications. Second, advanced heuristics that use more destroy operators in the spirit of adaptive large neighborhood search heuristics may be devised.

Appendix A. Mathematical formulation

<u>Sets and input parameters:</u>

$\mathcal{N}$	Set of affected areas indexed by i, j
$\mathcal{N}_0$	$\mathcal{N} \cup \{0\}$
$\{1, \dots, V\}$	Set of paths indexed by v
g	possible path length $g \in \{1, \dots, \lvert\mathcal{N}\rvert - V + 1\}$
$\{1, \dots, g\}$	Set of positions of traversed links indexed by q
p_i	The absolute utility score assigned to affected area i
$\tilde{d}_{(i,j)}$	Travel time over link (i, j)

Decision Variables:

$$x_{i,j,q}^{g,v} = \begin{cases} 1 & \text{If (i,j) is the q}^{\text{th}}\text{ link over the path of the vehicle } v \text{ with length } q \\ 0 & \text{otherwise} \end{cases}$$

Here, we present a mathematical formulation based on position-dependent variables (Dewilde et al., 2013) as follows.

$$\max: \sum_{v=1}^{V} \sum_{g=1}^{|\mathcal{N}|-V+1} \sum_{q=1}^{g} \sum_{i\in\mathcal{N}_0} \sum_{\substack{j\in\mathcal{N}\\ j\neq i}} \lambda \left[p_j - (g+1-q)E\big(\tilde{d}_{(i,j)}\big)\right] x_{i,j,q}^{g,v} -$$

$$-(1-\lambda)\sqrt{\sum_{v=1}^{V} \sum_{g=1}^{|\mathcal{N}|-V+1} \sum_{q=1}^{g} \sum_{i\in\mathcal{N}_0} \sum_{\substack{j\in\mathcal{N}\\ j\neq i}} \mathrm{VAR}\big(\tilde{d}_{(i,j)}\big) x_{i,j,q}^{g,v}} \quad (1)$$

$$\sum_{g=1}^{|\mathcal{N}|-V+1} \sum_{j\in\mathcal{N}} x_{0,j,1}^{g,v} = 1, \quad v = 1,\dots,V \quad (2)$$

$$\sum_{\substack{i\in\mathcal{N}_0\\ i\neq j}} x_{i,j,q}^{g,v} - \sum_{\substack{i\in\mathcal{N}\\ i\neq j}} x_{j,i,q+1}^{g,v} = 0, \quad j \in \mathcal{N},\ g = 2,\dots,|\mathcal{N}|-V+1, \quad q = 1,\dots,g-1, \quad v = 1,\dots,V \quad (3)$$

$$\sum_{g=q}^{|\mathcal{N}|-V+1} \sum_{i\in\mathcal{N}_0} \sum_{\substack{j\in\mathcal{N}\\ j\neq i}} x_{j,i,q}^{g,v} \leq 1, \quad q = 1,\dots,g, \quad v = 1\dots,V \quad (4)$$

$$\sum_{v=1}^{V} \sum_{g=1}^{|\mathcal{N}|-V+1} \sum_{q=2}^{g} \sum_{j\in\mathcal{N}} x_{0,j,q}^{g,v} = 0, \quad (5)$$

$$\sum_{v=1}^{V} \sum_{g=1}^{|\mathcal{N}|-V+1} \sum_{q=1}^{g} \sum_{\substack{i\in\mathcal{N}_0\\ j\neq i}} x_{i,j,q}^{g,v} \leq 1, \quad j \in \mathcal{N} \quad (6)$$

$$x_{i,j,q}^{g,v} \in \{0,1\},\ i \in \mathcal{N}_0,\ j \in \mathcal{N},\ g = 1,\dots,|\mathcal{N}|-V+1,\ q = 1,\dots,g,\ v = 1,\dots,V \quad (7)$$

The objective (1) maximizes the total utility. The set of constraints in (2) ensure the departure of all vehicles from the depot. The connectivity constraints are reported in (3). Constraints (4) guarantee that each position over each path is assigned to at most one link. The set of constraints in (5) establish that no link starting from the depot can be used in any other position except the first one, over each feasible path. The set of constraints in (6) require that each affected area is visited at most once over all paths. The set of constraints in (7) express the binary nature of variables.

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