Available online at www.sciencedirect.com

ScienceDirect

Procedia - Social and Behavioral Sciences 111 (2014) 918 – 926

Procedia
Social and Behavioral Sciences

EWGT2013 – 16th Meeting of the EURO Working Group on Transportation

The Gateway Location Problem: a cost oriented analysis of a new risk mitigation strategy in Hazmat Transportation

Paola Cappanera[a], Maddalena Nonato[b,*]

[a]*Dipartimento di Ingegneria dell'Informazione, Università degli Studi di Firenze, Via di Santa Marta 3, Firenze 50139, Italy*
[b]*Dipartimento di Ingegneria, Università degli Studi di Ferrara, Via G. Saragat 1, Ferrara 44100, Italy*

Abstract

Modern societies rely upon massive supplies of large amounts of commodities, some of which imply the use of hazardous materials (hazmat). A crucial step in the hazmat life cycle is transportation. An accident en route is a "low probability - high consequences" event and much effort has been devoted to the development of risk mitigation strategies. In this paper we are concerned with hazmat transportation by truck on a road network, where several alternative itineraries from origin to destination are worthy of choice. Given a set of origin-destination pairs and the hazmat quantities to be transported for each pair, the road network topology, and the cost and the risk of each arc, the aim is to reduce the total risk related to the hazmat itineraries, hopefully not to a sensitive detriment of cost.
In a mixed urban setting, the shortest path is often a risky one. Whenever possible, the network administrator imposes to each driver a specific itinerary with lower risk. If not possible, the network administrator may enforce some restrictions regarding network usage, such as forbidding hazmat transit on some links or imposing tolls.
Within this framework, we propose a new method that diverts vehicles from their shortest (and risky) path from origin to destination, by forcing each vehicle to pass through an intermediate check point, so called gateway. We face the problem of selecting the location of a given number of gateways among a larger number of potential locations and assigning a gateway to each vehicle such that the total risk is minimized. Once gateways are located and assigned, the "rational" driver will travel along the shortest path from its origin to its assigned gateway, and then from such a gateway to its destination.
While previous studies have experimentally demonstrated the efficacy of our strategy, the issue of the cost of the solutions has never been analyzed in depth. In this work we describe how to efficiently compute the Pareto frontier given by the non dominated solutions with respect to total risk and total cost on realistic instances taken from the literature, and we present computational results showing that the solution yielded by our method represents a very good compromise between the two criteria since it achieves substantial risk mitigation while providing an efficient trade off with cost.

© 2013 The Authors. Published by Elsevier Ltd.
Selection and/or peer-review under responsibility of Scientific Committee

Keywords: Hazardous materials transportation; risk mitigation; gateway location; Pareto frontier.

* Corresponding author. Tel.: +39-0532-974994; fax: +39-0532-974870.
E-mail address: maddalena.nonato@unife.it

1877-0428 © 2013 The Authors. Published by Elsevier Ltd.
Selection and/or peer-review under responsibility of Scientific Committee
doi:10.1016/j.sbspro.2014.01.126

1. Introduction

Any material posing a significant hazard to human health and safety or to the environment if accidentally released or improperly disposed of, can be considered as an hazardous material (hazmat). Despite of their potential harm, we can not get rid of hazardous materials since they are essential to our daily life and, more in general, to the economy of industrialized countries. Hazardous materials fuel our cars and make our lives comfortable, not to mention the many activities we carry on daily at our home that involve the use of solvents, pesticides, drain cleaners, or paints, just to mention a few. Hazmat also are necessary for farming, health treatments, manufacturing, mining, and most industrial processes. All these substances need to be carried from their production sites to the place where they are used in a safe and proper manner, or are the result of specific processes and must be properly disposed of after usage and collected (think of a radioactive medical treatment). A large amount of explosive, poisonous, corrosive, flammable, and radioactive materials are transported every day. While most hazardous material shipments arrive safely at destinations, those very few accidents during the transportation may cause considerable damage and ignite harsh protests among the affected population. These accidents en route belong to the class of so called low probability – high consequences events, i.e., while unlikely they cause considerable damage when they take place. Therefore, hazmat transportation poses several challenges to decision makers, including how to influence carrier decisions regarding shipments itineraries.

When the central authority in charge of safeguarding the transportation security within hits jurisdiction has the power to dictate and enforce one mandatory itinerary for each shipping, then the main issue is seeking a compromise between risk and equity: in so called *local routing problems*, the total risk related to multiple shipments between the same origin-destination pair should be minimized while equitably distributed over the whole region concerned (Akgün et al., 2000; Dell'Olmo et al., 2005). In order to obtain a collaborative attitude by carriers, cost must also be considered, often leading to multi-objective multi-commodity flow problems when modeling *global routing problems*, where shipments involve different origin-destination pairs (Huang et al., 2005; Zografos and Davis, 1989). All these approaches return a set of specific itineraries, one for each shipment, to be assigned to carriers. Enforcing a specific itinerary means that the shipment has to be constantly monitored, usually by the use of remote control sensors on board of the vehicle, which raises privacy issues and involves high costs of management. We refer to this framework as to the *over regulated scenario*.

A strategy which is alternative to the direct control on each shipment, as it is required in the over regulated scenario, can be realized by introducing some regulations, that is, a set of mandatory rules to which all carriers must comply. Such rules not only must be easy to implement, but must be devised in such a way that carriers response will result in a less risky set of itineraries. We refer to this case as to the *rule based scenario*. Several alternatives arising in this framework have been explored in the literature, ranging from modifying the set of feasible itineraries by banning hazmat transit on some links of the road network to altering the carrier utility function (usually a transportation cost) and then letting carriers free to adjust to such rules when optimizing their utility function. In this paper we deal with a new strategy recently proposed within the rule based scenario, which involves the solution of a new challenging combinatorial optimization problem, the Gateway Location Problem (GLP). Here we recall the methodology and present computational results on realistic instances that show that our strategy, beside being an effective risk mitigation tool, is also cost-effective. To this purpose, we present a methodology to easily compute the best trade off solutions between risk and cost, and we compare our solution against them.

The paper is organized as follows. In Section 2 we first recall the main contributions in the area of risk mitigation policies in a rule based scenario and describe the GLP. The issue of cost in the evaluation of solution quality is raised in Section 3, where we discuss how to efficiently compute the Pareto frontier of a bi-criteria problem, involving risk as well as cost. Computational results are presented in Section 4 where conclusions are drawn.

2. The gateway location problem: a new risk mitigation strategy in the rule based scenario.

2.1. A short review of risk mitigation policies proposed in the rule based scenario

As a general statement, we are concerned with hazmat transportation by truck on a road network, where several alternative itineraries from origin to destination are worthy of choice. Given a set of origin-destination pairs and the hazmat quantities to be transported for each pair, the road network topology, and the cost and the risk of each arc, the network authority issues some prescriptions so that the itineraries that compliant carriers will follow have a lower total risk with respect to the one achieved in the unregulated scenario (where carriers travel along the cheapest itineraries), hopefully not to a sensitive detriment of cost. Any strategy belonging to the rule based scenario must encompass into the problem the driver reactions to the authority prescriptions, which usually leads to bi-level optimization problems. Indeed, some studies specifically focus on the complicating issues arising in bi-level optimization.

The most popular measure aiming at mitigating hazmat transport related risk, is to forbid hazmat transit on some links of the road network. It can be a permanent veto as well as a temporary interdiction (the ban on hazmat transit across the Ambassador Bridge near Detroit, MI, will soon be lifted), or even a selective measure that allows the transit of some shipping while forbidding others. The selection of the best links to be closed is known of as the Hazmat Network Design (HND) Problem and its study has given rise to a few papers in the last few years. In their seminal work, Kara and Verter (2004) provide the first bi-level formulation of HND: in the upper-level problem the authority selects the links to be closed according to risk minimization, whereas the lower-level problem models carriers route choices that pursue cost minimization. Erkut and Alp (2007) stress the challenges posed by a bi-level formulation of the HND problem due to the existence of hill posed instances, where several itineraries of minimum cost exist which differ concerning risk. To overcome this obstacle, they propose to leave open to hazmat transit a tree shaped sub-network of the road network, so that for each commodity there is a unique path available from origin to destination. The sub-network is chosen heuristically, according to a greedy algorithm, so that the sum of the risk of the unique origin-destination path of each commodity is minimized. For the general HND, Erkut and Gzara (2008) propose a fast heuristic algorithm which guarantees stable solutions, i.e., solutions such that no commodity has multiple minimum cost paths with different risk values. To take into account carriers preferences, Verter and Kara (2008) introduce a single level path-based formulation, making explicit the set of paths acceptable to carriers and their preferences within such set.

Beside arc interdiction, another rule-based risk mitigation approach exploits *toll-setting*. In Marcotte and Savard (2009) tolls are used to deter hazmat carriers from using certain roads and to channel the shipments on less-populated roads. This policy also gives rise to a bi-level problem, which can be reformulated and solved as a single-level Mixed Integer Linear Programming (MILP) problem. The authors experimentally show the effectiveness of such a technique. Wang, Kang, Kwon, and Batta (2012) address the issue of traffic congestion as a matter of risk and cost, when hazmat vehicles and regular vehicles share the same infrastructure. A dual toll setting policy with linear delay is presented, aiming to minimize the total transportation cost and risk over the whole network. The resulting mathematical program with equilibrium constraints is reduced to a two stage problem for which a solution procedure is presented. Computational results on realistic instances are promising.

2.2. The Gateway Location Problem

In Bruglieri, Cappanera, Colorni and Nonato (2011) a third alternative policy was proposed for indirectly regulating hazmat transport, which consists of detouring vehicles through compulsory check points. This policy gives rise to the Gateway Location Problem (GLP). GLP consists of diverting vehicles away from their shortest path from origin to destination by assigning to each vehicle a compulsory crossing point, so called gateway, to be visited along its itinerary. Gateways must first be located at k sites, selected among $m>k$ potential locations on the network. Then, each vehicle is assigned a gateway. Each driver optimizes his/her utility function by following the shortest path from the origin to the assigned gateway and then from the gateway to destination. The solution value is the sum over all vehicles, of the risk of the selected itineraries multiplied by the shipment demand. The problem can be formalized as follows.

Let $V = \{1..n\}$ be the set of vehicles to be considered, each one going from its origin o_v to its destination d_v and shipping a quantity φ_v of hazardous material. Let N^{CS} denote the set of the m candidate sites, and let $G = (N,A)$ be a weighted directed graph with $O \cup D \cup N^{CS} \subseteq N$, where $O = \{o_v: v \in V\}$ and $D = \{d_v: v \in V\}$, and $A \subseteq N \times N$. For each arc $(i,j) \in A$, let c_{ij} and r_{ij} denote the cost and the risk coefficient, with $c_{ij} > 0$ and $r_{ij} \geq 0$ $\forall$ $(i,j) \in A$. The cost coefficients model the driver utility function and can be associated with distance, time, monetary cost, or any other such function. Risk coefficients model the potential damage related to shipping a unit of hazardous material along the arcs, and define the authority objective function. For sake of readability, we consider a simplified framework where such coefficients are equal for all shipments, that is, all shipments concern the same commodity, but the discussion can be generalized to handle a vehicle or a commodity dependency. In such a case unitary costs and risk coefficients would vary according to v. Moreover, we use interchangeably the terms vehicle, driver, carrier, and shipping to refer to an item v. Finally, let ρ_v^c and ρ_v^r denote the c-optimal and the r-optimal origin - destination path for each vehicle v. Moreover, ρ_v^c (ρ_v^r) are also referred to as the *shortest* (*safest*) path for vehicle v.

Let $gtw(v)$ denote the gateway assigned to vehicle v. Any path from o_v to d_v through $gtw(v)$ is called a gateway path for vehicle v. Once location $h \in N^{CS}$ has been selected to host a gateway, and gateway h has been assigned to vehicle v, i.e., $gtw(v) = h$, then vehicle v will travel along the shortest gateway path with respect to h, which is denoted by $\rho_v(h)$. In particular, $\rho_v(h)$ is made by two paths, namely the upstream gateway path $\uparrow\rho_v(h)$, i.e., the shortest path going from o_v to h, and the downstream gateway path $\downarrow\rho_v(h)$, i.e., the shortest path going from h to d_v. Indeed, both $\uparrow\rho_v(h)$ and $\downarrow\rho_v(h)$ are optimal according to c due to the rational driver behavior hypothesis. GLP can be described as the problem of selecting a subset N^{gtw} of size k out of the m sites in N^{CS} and assigning to each vehicle v one gateway $h \in N^{gtw}$ so that the sum over each vehicle of the risks of the two paths $\uparrow\rho_v(h)$ and $\downarrow\rho_v(h)$ is minimized. More formally, we solve the following combinatorial optimization problem GLP:

$$\min \sum_{v\in V} \sum_{h\in N^{gtw}|h=gtw(v)} \left(\sum_{(ij)\in\uparrow\rho_v(h)} r_{ij} + \sum_{(ij)\in\downarrow\rho_v(h)} r_{ij}\right)\varphi_v \quad \text{such that}$$

$$\sum_{h\in N^{gtw}|h=gtw(v)} z_v^h = 1 \quad \forall v \in V$$

$$N^{gtw} \subseteq N^{CS}$$

$$\left|N^{gtw}\right| = k,$$

where Boolean variables z_v^h are equal to 1 if node h is the gateway assigned to vehicle v. In case no gateway path can decrease the risk of ρ_v^c we let the vehicle free to follow its shortest path from origin to destination (a slight change in the model accounts for this possibility, that we call *exemption*). Actually, exemption is quite important, since it guarantees that the risk value associated with any optimal solution of the GLP will never increase the risk level achieved in the unregulated scenario. Finally, note that GLP is a hierarchical decision problem since both expressions $\uparrow\rho_v(h)$ and $\downarrow\rho_v(h)$ hide a nested level of optimization. Indeed, the minimum risk solution has to be searched for in the rational reaction set of the drivers.

Fig.1 depicts a toy network with six nodes, weighted by risk and cost coefficients on the arcs, where vehicle 1 has to travel from node 1 to node 6. The safest path ρ_1^r = (1,2,5,6) and the shortest path ρ_1^c = (1,2,4,6) are both depicted by dashed lines, the former in green and the latter in red. The gateway path $\rho_1(3)$ is shown in yellow: recall that $\rho_1(3)$ is the path that vehicle 1 would follow if gateway 3 were assigned to it. In particular, $\uparrow\rho_1(3)$ = (1,3) and $\downarrow\rho_1(3)$ = (3,5,6). It can be noted that traveling along $\rho_1(3)$ reduces the risk due to vehicle 1 from 24, i.e., the risk of ρ_1^c, to 15, which is not so greater than 14, i.e., the risk of ρ_1^r. At the same time, though, the cost of path $\rho_1(3)$ is much lower than 23, i.e. cost of ρ_1^r, and it only rises from 13, the cost of ρ_1^c, to 18.

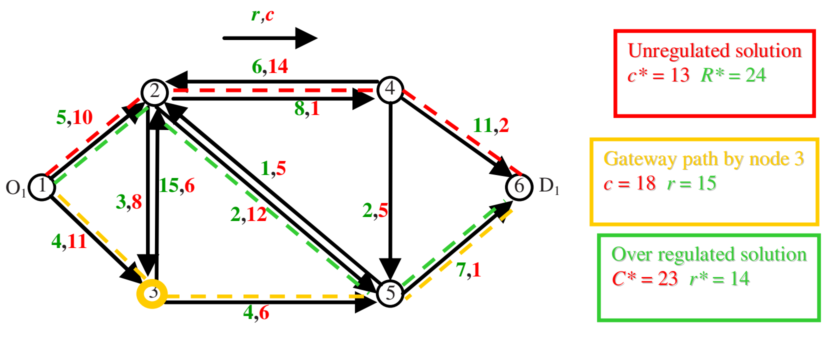

Fig. 1. A toy network with 6 nodes and a shipment from node 1 to node 6. The shortest path and the safest path are depicted, as well as the gateway path through node 3. It can be seen that traveling along this gateway path drastically decreases the risk due to this shipping with respect to the risk due to the shortest path while cost increases much less than what risk decreases.

To the best of our knowledge, GLP had never been studied before nor used in the context of risk mitigation. In Bruglieri, Cappanera, Colorni, and Nonato (2011) three mathematical formulations of GLP were proposed: a path based ILP model, a *k-median* like ILP model, and a bi-level *multicommodity flow* model, together with its reduction to a single level MILP. In particular, in the experimental campaign described in Section 4 we will adopt the so called *k-median* like MILP model. All models assume to be given the candidate sites set N^{CS}, i.e., the set of the sites where a gateway is potentially installed. In Bruglieri, Cappanera, and Nonato (2013) the impact of this preparatory phase of GLP was addressed, and an information guided policy for the generation of this set was proposed and experimentally validated.

This paper documents a further step along this line of research, where we address the issue of cost. We believe that the efficacy of a risk mitigation policy for hazmat transport has to be evaluated by taking both risk and cost into account. Indeed, a strategy that produces very safe but very expensive itineraries, will never be adopted by carriers who will oppose it and perceive risk mitigation as a detriment to their business. Indeed, the GLP based strategy leaves a certain degree of freedom to drivers who select their shortest gateway path once they are assigned a gateway. This is not only required in order to properly model drivers' response to mandatory rules, but it has been planned on purpose as part of the strategy, as a safeguard to cost deterioration. However, this second effect is not a priori guaranteed and must be verified ex post, as we will do in the next section.

3. Building the Pareto frontier of a bi-criterion problem

A first way of evaluating the quality of a GLP solution is based on the ranking of such a solution with respect to the scores of the solutions obtained in the two extreme situations, i.e., on the one hand, in the unregulated scenario where each driver travels along the shortest path from origin to destination, and on the other hand, in the overregulated scenario where each vehicle is forced to follow the safest path. Let the pairs $<c^*, R^*>$ and $<C^*, r^*>$ denote the risk and the cost values associated with the solution computed in the unregulated and the over regulated scenario, respectively. Such solutions provide a range $[r^*, R^*]$ and $[c^*, C^*]$ for the feasible values of risk and cost, respectively: risk should be not higher than the risk of the itineraries that drivers follow when unconstrained and it can not be lower than the minimum achievable one. Likewise, cost should not be greater than the one related to the safest itineraries while it cannot be below the minimum one. When assessing the quality of a solution with score <r, c>, a first step is to frame the cost and risk values in the respective ranges and evaluate the percentage decrease with respect to the maximum risk and the percentage increase with respect to the minimum cost, scaled by the range width. In Section 4 we carry out this analysis with respect to the GLP solution.

However, in our opinion, the solution evaluation step deserves a deeper understanding. Cost deterioration due to risk mitigation policies is a potential deterrent to the widespread application of such policies by the carriers, therefore we claim that the issue of cost can not be ignored when assessing the effectiveness of a risk mitigation strategy. This reasoning naturally leads to a bi-criterion optimization problem perspective. However, we argue that considering as a reference only the two extremes, i.e., the points $<c^*, R^*>$ and $<C^*, r^*>$, might be misleading since the analysis could be biased by the wrong assumption that the best solutions are all obtained by a convex combination of such points, namely the points $\in R^2$ of coordinates $<r(\lambda), c(\lambda)> = <c^*+(C^*-c^*)\lambda , r^*+(R^*-r^*)(1-\lambda)>$, with $\lambda\in [0..1]$, that lie on the segment in the plane comprised between $<c^*, R^*>$ and $<C^*, r^*>$. Actually, we believe that a carrier should be convinced that the raise in cost that it has to face in order to comply with the authority rules, is fully compensated by a risk decrease, that is, risk could not be further decreased at the same cost. The challenge is to device a strategy that fulfills these requirements and it is easy to implement at the same time. A more meaningful analysis requires the computation of the Pareto frontier of the bi-criterion problem with respect to risk and cost minimization, that is, the set $S\subseteq R^2$ made by all the pairs <r', c'> that are not dominated in the Pareto sense and such that r' and c' correspond to the sum over all vehicles of the risk and the cost of an origin-destination path for that vehicle, respectively. In general, the shape of the piece wise linear function that links the points in S has several kink points and therefore may substantially differ from the abovementioned segment.

More formally, S is given by the Pareto frontier of the following bi-criterion problem. For each vehicle $v\in V$, let P_v denote the set of the path from o_v to d_v, and let x_v^p be the Boolean variable associated with path $p\in P_v$, i.e., x_v^p is equal to 1 *iff* vehicle v travels along path p and 0 otherwise. Let r_v^p and c_v^p be the risk and the cost of path $p\in P_v$, respectively. Then the set S of the best trade offs between risk and cost is given by the optimal solutions of problem P, where

$$P: \quad \min \frac{\sum_{v\in V}\left(r_v^p x_v^p\right)\varphi_v}{\sum_{v\in V}\left(c_v^p x_v^p\right)\varphi_v} \quad \textit{such that} \quad \sum_{p\in P_v} x_v^p = 1\ \forall v\in V$$

It is easy to see that any path p such that $x_v^p = 1$ must be loopless. In fact, the cost coefficients of the arcs of the network are positive; risk coefficients are non negative, so that for each vehicle and for each origin-destination path with a zero-risk cycle, a loopless dominating path with the same risk exists. Furthermore, it can also be proved by contradiction that, for each point in S, the cost and risk of the selected path for vehicle $v\in V$ belongs to the Pareto frontier S_v made by the non dominated solution values of the paths from o_v to d_v. Brumbaugh-Smith and Shier (1989) discuss and compare several pseudo-polynomial algorithms to be used for computing S_v. In the following we describe how S can be efficiently computed by solving a bi-criterion shortest path, by way of any such algorithm, on a layered graph, given that all sets S_v have been computed.

Let $G^V=(N^V, A^V)$ be a layered graph with 2+n layers, where $n=|V|$, such that $N^V = \cup_{v\in V} S_v \cup \{s, e\}$, where s and e are two fake nodes denoting the start and the end of the graph, respectively. $A^V = \cup_{v\in\{1..n-1\}} \{S_v \times S_{v+1}\} \cup A_s \cup A_e$, where $S_v\times S_{v+1}$ is the set of arcs connecting a node associated with a Pareto optimal path in S_v to a node associated with a Pareto optimal path in S_{v+1}. Moreover, let $A_s= \{s \times p \mid p \in S_1\}$ and $A_e= \{p \times e \mid p \in S_n\}$. Each arc in A^V has cost and risk coefficients equal to the cost and risk of the path associated with the tail node multiplied by the vehicle demand, except for the arcs in A_s featuring null coefficients. Any path from s to e in G^V identifies one Pareto optimal path for each vehicle. Solving a bi-criterion shortest path on G^V solves problem P.

Regarding the toy network depicted in Figure1, note that there are 4 Pareto optimal paths from o_1 to d_1, namely the shortest path ρ_1^c = (1,2,4,6), path (1,2,4,5,6), the gateway path $\rho_1(3)$ = (1,3,5,6), and the safest path

ρ_1^r = (1,2,5,6), whose risk and cost are <24, 13>, <22, 17>, <15, 18>, and <14, 23>, respectively. Therefore, the associated layered graph G^V would have 4 nodes at second layer, the one associated with S_1.

It is easy to see that the set of the Pareto optimal paths from *s* to *e* corresponds to the set *S* of all the efficient trade offs between risk and cost of the system as a whole. We claim that the GLP solution should be compared against the frontier of such a set. In Section 4 we present computational results concerning this analysis on realistic instances.

4. Computational results: how far are GLP solutions from the Pareto optimal ones?

The experimental campaign was carried out on the same set of instances described in Erkut and Gzara (2008), where the network topology is an abstraction of the road network of Ravenna (Italy) with 105 nodes, 134 undirected arcs, and 35 origin-destination pairs. Furthermore, the demand for each shipment and the cost for each arc are given. Three different risk functions are considered, as in Erkut and Gzara (2008), namely, *aggregate*, *around-arc*, and *on-arc*. On these instances the Pareto optimal paths were computed via an implementation of the algorithm proposed in Brumbaugh-Smith and Shier (1989); running times are negligible being in the order of few milliseconds and thus they are not reported.

In regards to the candidate gateway nodes, which are a peculiarity of our methodology, we generated 10 samples of the set N^{CS} via a policy that first identifies a ground set of nodes out of which the selection probability of a node is null and then adopts a distribution law for sampling the ground set. Specifically, the ground set is made of all those nodes that, vehicle by vehicle, belong to the safest path and not to the shortest path; in this case we say that the vehicle sponsors such nodes. The distribution law attributes to each node a weight that is proportional to the number of vehicles sponsoring it and to vehicle demand. For further details on the generation policy, the reader is referred to Bruglieri, Cappanera and Nonato (2013) where the policy above described is denoted by (C_2, ϕ_3). There, an extensive computational testing shows that such a policy represents a very good compromise between efficacy and robustness. Once the candidate site set N^{CS} is identified, with $|N^{CS}|$ = 30% |N|, the corresponding GLP is solved for the number *k* of gateway nodes to open fixed to the value for which the marginal improvement of the risk mitigation level is negligible (these values are respectively 5, 3 and 4 for aggregate, around-arc, and on-arc risk measure). Also the computational time required to solve a GLP instance are negligible and they are not reported here.

Table 1. How GLP solution ranks in risk-cost range

Risk measure	r^*	r	R^*	c^*	c	C^*
aggregate	124,854,028	396,203,057	2,208,839,655	2,508,138,643	3,363,902,431	5,661,988,958
around-arc	2,024,247,704	2,079,803,990	7,229,256,314	2,508,138,643	2,929,192,816	3,109,417,898
on-arc	499,767,899	514,839,597	567,773,424	2,508,138,643	2,822,683,224	3,498,145,748

In Table 1 GLP solutions are ranked in risk range [r^*, R^*] and in cost range [c^*, C^*]. Specifically, r^* and c^* denote respectively the average risk and cost values of GLP solution, rounded to the integers, computed on the 10 samples. Consider that the percentage gap between the minimum and the maximum risk, i.e., $(R^*- r^*)/ r^*$, is 1661.14%, 257.13%, and 13.61%, for the aggregate, around-arc, and on-arc risk measure, respectively. Each such value provides an indication of how much room there is for improvement with respect to risk mitigation, for each risk measure. By making r^* 0 and R^* 100, our reference solution, obtained by policy (C_2, ϕ_3) as mentioned before, ranks at 13.02%, 1.07%, and 22.16%, for the aggregate, around-arc, and on-arc risk measure, respectively. The same results are obtained when N^{CS} = N.

In regards to the cost range, the figures are the following: the percentage gap between the minimum and the maximum cost, i.e., $(C^{*}- c^{*})/ c^{*}$, is 125.74%, 23.97%, and 39.47%, for the aggregate, around-arc, and on-arc risk measure, respectively. By making c^{*} 0 and C^{*} 100, our reference solution ranks at 27.13%, 70.03%, and 31.77%, for the aggregate, around-arc, and on-arc risk measure, respectively. Observe that the highest of such percentages, i.e. 70.03%, occurs in correspondence with the smallest percentage cost gap.

It can be noted that when the risk window is large there is room for improvement and indeed we achieve large risk reductions while controlling costs. However, when the unregulated solution is not very different from the over regulated one, i.e., the window is narrow, our method is still able to reach almost 80% of the achievable risk reduction.

The capability of the GLP approach of identifying a very good tradeoff between risk and cost is even more evident by looking at how the GLP solution ranks with respect to the frontier made of he Pareto optimal paths. Specifically, Figures 2, 3, and 4 represent the position in terms of cost (*x*-axis) and risk (*y*-axis) of the GLP solution (square box) with respect to the Pareto optimal paths (diamond boxes), respectively for aggregate, around-arc and on-arc risk function. For readability, in the following figures cost and risk are scaled with respect to the values shown in Table 1. Note that a gateway path is not necessarily a Pareto optimal one. Nevertheless, it is worth observing that the GLP solution is very close or even on the Pareto frontier and, as desirable, it is located on the point where the curve of the frontier mostly changes its slope whatever the risk measure.

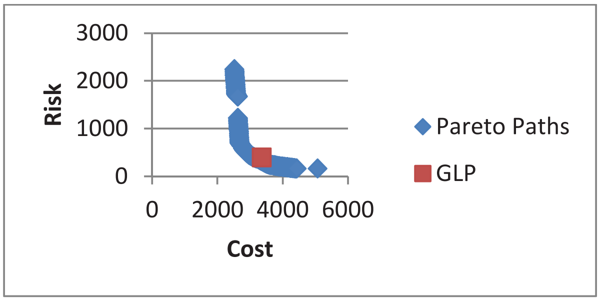

Fig. 2. Aggregate risk function

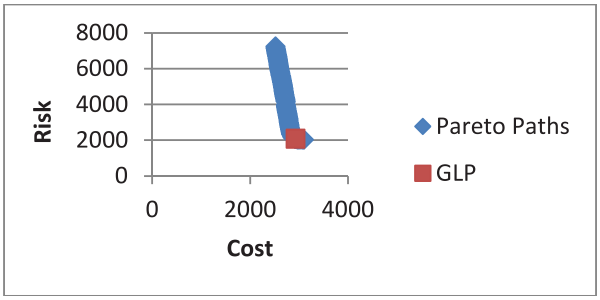

Fig. 3. Around arc risk function

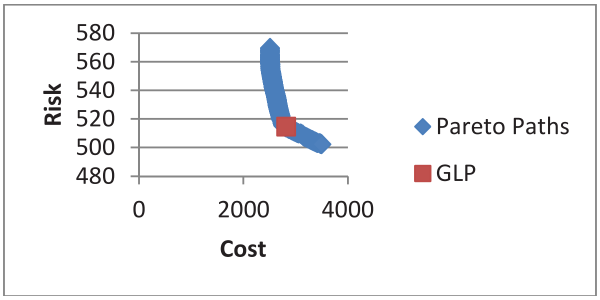

Fig. 4. On arc risk function

Acknowledgements

We are grateful to Mirko Maischberger for lending us his implementation of the algorithm described in Brumbaugh-Smith and Shier (1989).

References

Akgün, V., Erkut, E., & Batta, R. (2000). On finding dissimilar paths. *European Journal of Operational Research*, 121, 232 - 246.

Bruglieri, M., Cappanera, P., Colorni, A., & Nonato, M. (2011). Modeling the Gateway Location Problem for Multicommodity Flow Rerouting. In J. Paul, T. Reiners, & S. Voß (Eds.), *Proceedings of INOC 2011, Lecture Notes in Computer Science 6701* (pp. 262 - 276). Berlin: Springer.

Bruglieri, M., Cappanera, P., & Nonato, M. (2013). The Gateway Location Problem: assessing the impact of candidate site selection policies. *Discrete Applied Matehmatics*, forthcoming.

Brumbaugh-Smith, J., & Shier, D. (1989). An empirical investigation of some bicriterion shortest path algorithms. *European Journal of Operational Research*, 43(2), 216 - 224.

Dell'Olmo, P., Gentili, M., & Scozzari, A. (2005). On finding dissimilar Pareto-optimal paths, *European Journal of Operational Research*, 162(1), 70 - 82.

Erkut, E., & Alp, O. (2007). Designing a road network for hazardous material shipments. *Computers and Operations Research* 34, 1389 - 1405.

Erkut, E., & Gzara, F. (2008). Solving the hazmat transport network design problem. *Computers and Operations Research* 35, 2234 - 2247.

Huang, B., Fery, P., & Zhang, L. (2005). Multiobjective Optimization for Hazardous Materials Transportation. *Transportation Research Record: Journal of the Transportation Research Board* 1906(1), 64 - 73.

Kara, B.Y., & Verter, V. (2004). Designing a Road Network for Hazardous Material Transportation. *Transportation Science* 38(2), 188 - 196.

Verter, V., & Kara, B.Y. (2008). A path based approach for hazmat transport network design. *Management Science* 54(1), 29 - 40.

Wang, J., Kang, Y., Kwon, C., & Batta, R. (2012). Dual Toll Pricing for Hazardous Materials Transport with Linear Delay. *Networks and Spatial Economics* 12(1), 147 – 175.

Zografos, K.G., & Davis, C.F. (1989). Multiobjective programming approach for routing hazardous materials. *Journal of Transportation Eng.* 115(6), 661 - 673.