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A Bi-Objective Approach to Evaluate Highway Routing and Regulatory Strategies for Hazardous Materials Transportation

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Hazardous materials (hazmat) transportation is of concern to policymakers because of the serious safety, health, and environmental risks associated with the release of hazmat. One effective approach to minimize risks associated with hazmat transport is the prohibition of hazmat transportation on higher risk links that either pose safety hazards or increased exposure by traversing densely populated areas. Because of high risk, there are multiple stakeholders involved in hazmat transportation. While shippers and carriers are directly involved in making routing decisions, regulatory agencies influence this decision by imposing routing restrictions. In this paper, we apply a bi-objective shortest path problem to evaluate routing and regulation plans for hazmat transportation. We characterize the cost objective as the shortest path between an origin and a destination. The risk objective is to minimize the risk of exposure by restricting the link with the highest risk on the best available path from an origin to a destination. We formulate the bi-objective model and apply it to a test network. Solutions consider multiple origin-destination pairs and present a non-dominated frontier to establish routing and regulatory strategies for hazmat transportation.

INTRODUCTION

Transportation of hazardous materials (hazmat) poses risks because of the danger associated with the accidental release of hazardous materials. An incident involving a vehicle carrying hazardous materials can produce undesirable short- and lon-term consequences to human health and the environment, including severe illness, death, and irreversible pollution, and in the worst case may require evacuation. A recent United States Department of Transportation commodity survey reports that hazmat transportation on highways has increased by approximately 4% from 2002 to 2007 (U.S. Department of Transportation July 2010). Due to this increase in hazmat transportation and the negative consequences associated with these incidents, various risk mitigation strategies have been proposed to lower the probability and consequence of hazmat release into the environment. Effective methods in hazmat transport risk minimization identify minimum risk paths and eliminate hazmat transport on links where the risk of population or environmental exposure is unacceptably high.

Hazardous materials transportation is different from the conventional vehicle routing because of the risk associated with hazmat transportation. Hazmat routing is usually controlled by multiple criteria, making the routing suitable for multi-objective optimization (Chang et al. 2005). These criteria may be pursued by a single or a group of stakeholders. For example, shippers and carriers may want to find a route that minimizes transportation costs but at the same time minimizes risk to reduce liability. Regulatory agencies may restrict links where risk is excessively high, which may affect shippers' and carriers' route choice. Regulators may also want to make sure that the restriction is not imposing an overly burdensome transportation cost. Hence, there are two aspects in both routing and link restriction decisions: risk and cost. Bi-objective optimization can be effective for problems with two dissimilar objectives and in cases when the competing objectives have different units (e.g., risk and cost).

This paper proposes a bi-objective optimization model satisfying both risk and cost aspects of hazmat routing. In this model, one objective is to enhance network security by identifying critical links that shippers and carriers are likely to choose, in which risk exposure is unacceptably high. Risk is defined as the product of hazmat vehicle incident probability and the consequence of an incident. Consequence is defined as a link's neighboring population exposure. Routing risk is usually minimized by identifying minimum risk paths; however, because of the serious consequences associated with hazmat release, an incident on a single link can produce severe impacts even though that link is on the minimum risk path. Thus, avoiding the link with the highest risk may constitute a better risk aversion strategy than approaches that minimize aggregate path risk. The second objective is to determine a least cost path for hazmat transport. The combination of these two objectives requires a tradeoff between maximum link risk and minimum transportation cost. We employ a test network with synthetic data to illustrate the model. Multiple origin-destination pairs are considered. The effect of link restriction or avoidance of a particular link on the path choice is examined. The model output can be used to support decisions involving roadway and route restrictions in hazmat transport.

LITERATURE REVIEW

A widely accepted definition of hazmat transportation risk is the product of the probability of an incident and the consequence of this incident (Erkut and Ingolfsson 2000). Consequences of an incident can range from fatalities to infrastructure and environmental damage. Due to the complexity of enumerating all possible forms of loss and the fact that consequences are proportional to the population in the neighborhood of the incident, population exposure is often taken as the surrogate measure of risk. In the Federal Highway Administration guidelines for hazardous materials (Shaver and Kaiser 1998), population exposure has been viewed as the most important criterion in routing. Numerous hazmate routing problems have studied risk aversion using this definition. We also consider this definition in this paper.

List et al. (1991) provided a broad overview of hazmat transportation models, including risk analysis, routing and scheduling, and facility location prior to 1991 and observed a shift from single- to multi-objective optimization. Erkut and Verter (1998) discussed several risk models, all of which involve minimization of aggregate link risk at their core. They showed that optimal paths under one model could perform poorly under another model. Erkut and Ingolfsson (2000) introduced three somewhat different risk aversion objectives in a hazmat transportation model: minimizing the maximum population exposure, minimizing the variance of losses along a route, and minimizing the expected disutility of the losses. All three of these models can be characterized as shortest path problems. The authors concluded that the first of these three models may be the most intuitive and tractable.

Bi-level models have also gained popularity because they accommodate the two decision makers (government regulators and hazmat shippers/carriers) most directly involved in route planning. For example, Kara and Verter (2004) and Erkut and Gzara (2008) formulated bi-level models where the government selects a subset of available roads to minimize total risk and then allows carriers to choose routes that offer the shortest distance within the reduced network. The bi-level program of Bianco, Caramia, and Giordani (2009) considers multiple layers of government authority, responsible at different geographical levels, including regional and local authorities. In this approach, regional authorities seek to minimize the total risk in the area under their jurisdiction, while local authorities prefer to minimize the risk to the local population.

There exists a substantial literature related to transportation security and terrorism, and many of these studies apply game theory. A comprehensive review of game theoretic techniques in transportation can be found in Hollander and Prashker (2006). Network vulnerability assessment has also received significant attention. Bell (2006; 2007) formulated a two-person, non-cooperative,

zero-sum game in which the hazmat router seeks a shortest path assignment and the tester seeks to maximize network disruption. In this game, a shipper wishes to minimize the average population affected; while the demon desires to maximize the average population affected by creating an incident on one edge. This study demonstrated that a shipment possessing multiple routes between a single origin-destination pair reduces the risk of exposure more than shipments with only one available route. Nune and Murray-Tuite (2007) identify the possible routes taken by a demon hijacking a hazmat truck to maximize the consequences. They found that travel time rather than travel distance is a more appropriate criterion to identify the paths in urban areas during peak hours. Dadkar, Nozick, and Jones (2010) used a non-zero sum game structure between a shipper and a terrorist and maximize carrier utilities to optimize link use restrictions. The terrorist's link attack preference is influenced by the routes chosen by the carrier and the regulations implemented by the government. Given the carriers' choice of path and the terrorist attack strategy, the government then decides which links to prohibit. An extension of this study by Reilly et al. (2012) included a Stackelberg game in which the government acts as a leader to maximize the carrier's payoff and limit the terrorist's payoff. Rahman et al. (2012) showed that reducing the size of hazmat network may increase the attacker's expected payoff.

Similar to the bi-level modeling approach, the multi-objective path finding approach has gained attention as a method to model scenarios where there are several stakeholders. List and Mirchandani (1991) presented a multi-objective model for routing and facility location of hazardous materials considering travel time as a link attribute and risk as a zonal attribute. Nozick, List, and Turnquist (1997) introduced time varying patterns of accident rates and exposure into multi-objective routing and scheduling of hazmat transportation based on three minimization criteria: the accident rate, link population exposure, and route length. The authors examined the tradeoff between two criteria considering time varying and static patterns of accident and exposure. A time varying pattern was also explored by Miller-Hooks and Mahmassani (1998) and Chang, Nozick, and Turnquist (2005).

In this paper, we use a bi-objective model addressing both the cost and risk aspects of hazmat routing. A shortest path from origin to destination captures the minimum transportation cost objective. This objective is consistent with the Department of Transportation's routing guideline (U.S. Department of Transportation 1994) that endeavors to avoid imposing an excessive burden on commerce. The risk objective is to restrict or avoid links exhibiting high risk to exposure. That is, we seek to minimize the maximum risk within a path. This is different from the prevailing literature where routing is usually obtained by minimizing the total path cost. This paper proposes a method that can be used by regulators to obtain link regulation strategies and also by shippers and carriers to determine what routes should be avoided to reduce risk, yet strike a balance between cost and risk.

FORMULATION

Consider a directed transportation network, $G = (N, A)$, where N is a set of nodes and A is a set of m links. Each link is indexed by $(i, j) \in A : i, j \in N$. Hazardous materials are transported through from origins, to their destinations. The following notations and data are used in the model:

Data

$\quad P_{ij}$ = Population on a link (i, j) within a threshold distance

$\quad \rho_{ij}$ = Incident probability on a link (i, j)

$\quad c_{ij}$ = Hazmat transportation cost on a link (i, j)

$\quad \Omega_{ij}$ = $\rho_{ij} P_{ij}$ = Hazmat risk of link (i, j)

$\quad z_{ij}$ = $\begin{cases} 0, & \text{link } (i, j) \text{ is restricted to hazmat transport} \\ 1, & \text{link } (i, j) \text{ is open} \end{cases}$

The at-risk population P_{ij} is the population living within a specified threshold distance from the link. The impact radius varies for different types of hazmat ranging from 0.5 to 5.0 miles (US Department of Transportation 1994). Therefore, P_{ij} is defined as the population within 0.5 to 5.0 miles of a link (i, j) in all directions depending on the type of hazmat. It is assumed that on-link population is negligible. The restricted links where risk is excessively high are represented by z_{ij}. Some links may be closed *a priori* to prevent exposure to particularly sensitive populations (e.g., schools, government offices, hospitals). These links may require a well-coordinated evacuation plan in the event of an accident. Therefore, the regulator may decide to close them in advance to minimize the possibility of such scenarios. Also, even though the impact area is not circular, the analyst can consider the population within the impact area obtained from any diffusion pattern and use this model.

Decision Variable

$$x_{ij} = \begin{cases} 0, & \text{link } (i, j) \text{ is not used for hazmat transport} \\ 1, & \text{link } (i, j) \text{ is used} \end{cases}$$

The decision variable x_{ij} identifies the links included in the hazmat routes.

Bi-Objective Shortest Path Model

(1) P1 $\min \max_{(i, j) \in A} \Omega_{ij} \, x_{ij}$

(2) P2 $\min \sum_{(i, j) \in A} c_{ij} \, x_{ij}$

Subject to

(3) $\sum_{j: (i, j) \in A} x_{ij} - \sum_{j: (i, j) \in A} x_{ij} = \begin{cases} 1, & i \text{ is origin} \\ -1, & i \text{ is destination} \\ 0, & \text{otherwise} \end{cases}$
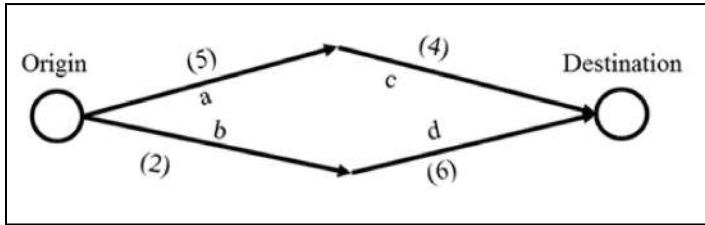
(4) $x_{ij} \leq z_{ij}$

(5) $x_{ij}, z_{ij} \in \{0,1\}$

Here, the two dissimilar objectives, referred to as P1 and P2, are given by equation (1) and equation (2). The first objective is a minimum maximum (minmax) formulation, whereas the second one is a minimum sum (minsum) formulation. The bi-objective formulation creates a minmax-minsum shortest path problem (Berman, Einav, and Handler 1990; de Lima Pinto, Bornstein, and Maculan 2009). Equation (3) is the flow balance constraint employed to find the shortest path between an origin and a destination. Equation (4) ensures that only links available to hazmat transport are selected by the carriers. Equation (5) is the binary requirements of the decision variable and initial link closure.

To illustrate the suitability of the model, consider a carrier wishing to transport a hazmat shipment from the origin to the destination in the network shown in Figure 1. The network consists of four links: *a*, *b*, *c*, and *d*, with two paths (*a*, *c*) and (*b*, *d*). All links possess equal travel time. The risk of an incident on each link is shown in parentheses and the incident probability is independent of the carrier's path choice. Although path risk is lower on path (*b*, *d*), the minmax-minsum model prefers path (*a*, *c*) because it avoids the maximum risk link *d* on the two paths available. Hazmat transportation is defined as a "low probability high consequence" event, where even a single incident in one million shipments can produce severe consequences. Thus, avoiding the link with the highest

risk may constitute a better risk aversion strategy than approaches that sum the risk of each link in a path.

Figure 1: Example Illustrating the Minmax-Minsum Model

SOLUTION PROCEDURE

In this paper, the algorithm proposed by Berman et al. (1990) is adapted to solve the program given by Eqs. (1) to (5). They considered network problems that are characterized by two performance measures. One performance measure is a cost function and the other is a maximum cost. In this algorithm, one or more links with cost above a certain value in the first problem are deleted from the network to obtain a reduced network. The second problem is solved on the reduced network. The algorithm continues until the origin and destination become disconnected from each other. The algorithm produces all solutions that satisfy both objectives and identifies all non-dominated (Pareto optimal) solutions. A solution is called a non-dominated solution when there is no alternative solution that is better than that solution with respect to any of the objectives. More detailed explanation of non-dominated solutions can be found in de Lima Pinto et al. (2009), Huang et al. (2005), and Erkut and Gzara (2008). The algorithm from Berman et al. (1990) is described below:

Step 0. Initialize the network by setting initial restrictions, z_{ij} if any. Set $F = \emptyset$. Here F is a set of all Pareto solutions (α^0, β^0). α^0 and β^0 correspond to the Pareto or non-dominated solutions of P1 and P2 respectively. Set $\beta^0 = \infty$.

Step 1. Rank all available links in the network in non-decreasing order of the link risk, Ω_{ij}. To do this, define a link with rank r, l^r, $r = 1, ..., m$, so that $\Omega_{ij}(l^1) \leq \Omega_{ij}(l^2) \leq \cdots \leq \Omega_{ij}(l^m)$. Here l^r represents ranked link and m is the number of links in the network. Set $r = m$.

Step 2. Set $\alpha_r = \Omega_{ij}(l^r)$. If there are other links l^k, $k < r$, with the same risk as $\Omega_{ij}(l^r)$ update r to be equal to the smallest such k. Delete from the network all links where $\Omega_{ij} \geq \alpha_r$. Solve $P2$ on the reduced network. Let the solution be β_r. If $\beta_r > \beta^0$ then $F = F \cup \{(\alpha^0, \beta^0)\}$. If no solution exists, stop.

Step 3. Set, $\beta^0 = \beta_r$, $\alpha^0 = \alpha_r$ and $r = r - 1$, if $r = 0$, then set $F = F \cup \{(\alpha^0, \beta^0)\}$ and stop, otherwise go to step 2.

The algorithm produces all feasible solutions (α_r, β_r) and identifies all the non-dominated solutions (α^0, β^0).

APPLICATION

We apply the MinMax-MinSum shortest path model to the Sioux Falls network (available at http://www.bgu.ac.il/~bargera/tntp/), a widely used case study employed in recent research, including Ukkusuri and Yushimito (2009) and Lownes et al. (2011) for network vulnerability analysis. Figure 2 shows the network, which consists of 24 nodes and 76 links. The analysis considers two origin nodes (nodes 2 and 3) and two destination nodes (nodes 18 and 22), resulting in four origin-destination pairs. The randomly generated synthetic link data used in this analysis are reported in Table 1. While generating the data, relatively higher populations were placed in the middle of the network, imitating a dense core with a lower density fringe.

Figure 2: Sioux Falls Network (Dashed Squares = Origins, Dashed Diamonds = Destinations)
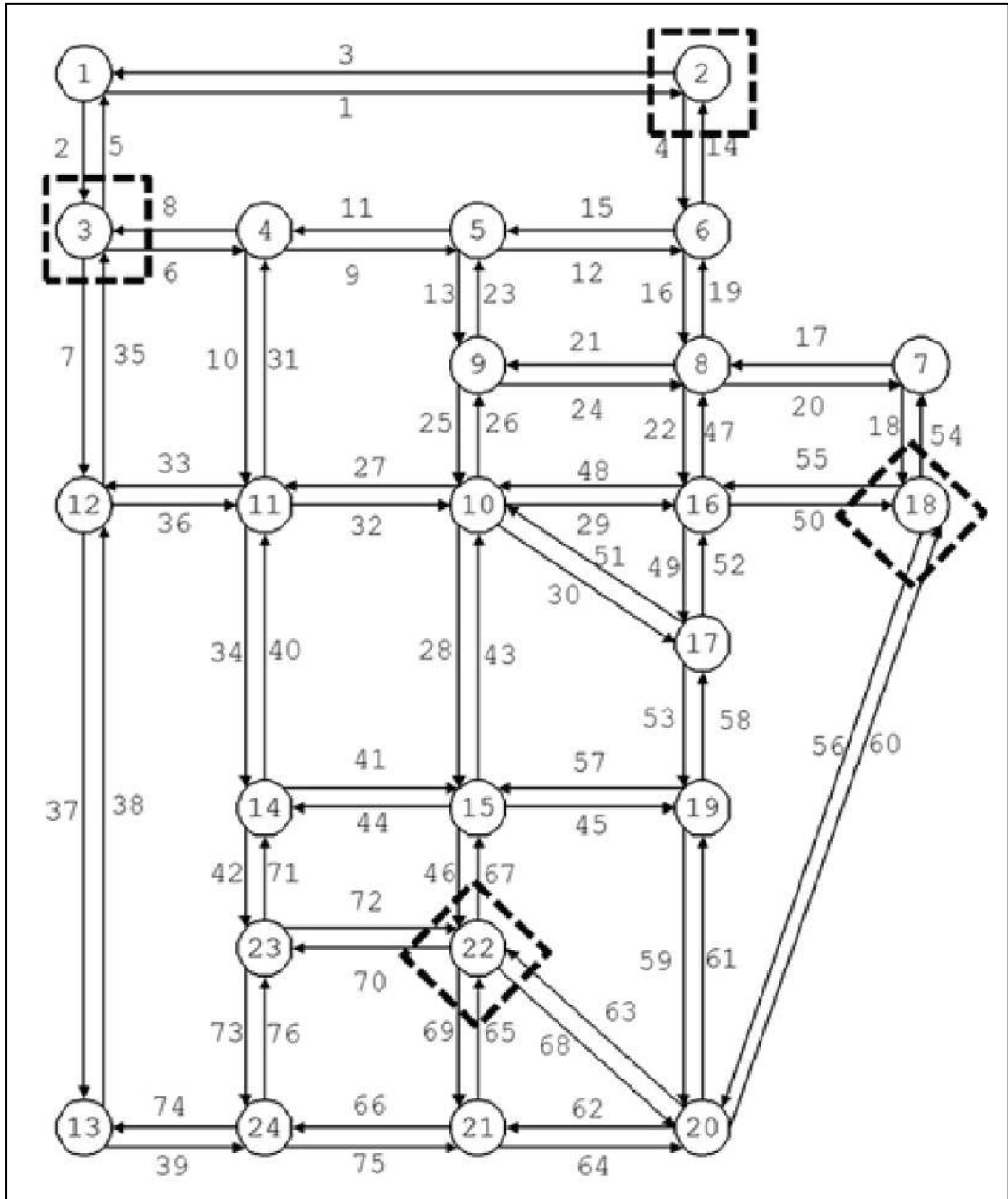
Table 1: Sioux Falls Network Data

Link ID	Travel Time (hr), c_{ij}	Population, P_{ij}	Incident Probability ($\times 10^{-8}$), ρ_{ij}	Risk ($\times 10^{-4}$), Ω_{ij}	Link ID	Travel Time (hr), c_{ij}	Population, P_{ij}	Incident Probability ($\times 10^{-8}$), ρ_{ij}	Risk ($\times 10^{-4}$), Ω_{ij}
1	0.40	10800	3.0	3.24	39	0.90	18400	9.0	16.56
2	0.30	9000	8.0	7.2	40	0.30	15100	6.0	9.06
3	1.00	10800	1.0	1.08	41	0.90	11800	8.0	9.44
4	0.20	9300	3.0	2.79	42	2.90	10500	1.0	1.05
5	3.20	9000	8.0	7.2	43	0.60	16000	3.0	4.8
6	0.20	13300	9.0	11.97	44	0.50	11800	8.0	9.44
7	0.10	7600	3.0	2.28	45	1.20	11300	7.0	7.91
8	0.40	13300	6.0	7.98	46	1.30	9200	8.0	7.36
9	0.20	14000	2.0	2.8	47	1.20	5200	5.0	2.6
10	1.70	11700	2.0	2.34	48	1.60	4800	7.0	3.36
11	1.70	14000	6.0	8.4	49	0.20	8700	9.0	7.83
12	3.20	11100	9.0	9.99	50	0.60	9100	7.0	6.37
13	1.70	9500	7.0	6.65	51	0.60	7800	6.0	4.68
14	3.20	9300	3.0	2.79	52	0.20	8700	9.0	7.83
15	0.30	11100	9.0	9.99	53	1.50	12300	8.0	9.84
16	1.10	5100	8.0	4.08	54	2.90	3400	5.0	1.7
17	0.30	12300	8.0	9.84	55	0.60	9100	7.0	6.37
18	0.90	3400	3.0	1.02	56	0.30	10400	4.0	4.16
19	0.50	5100	5.0	2.55	57	1.00	11300	7.0	7.91
20	0.20	12300	8.0	9.84	58	0.70	12300	8.0	9.84
21	1.70	6000	7.0	4.2	59	0.90	12200	4.0	4.88
22	3.20	5200	1.0	0.52	60	0.50	9600	9.0	8.64
23	0.30	9500	6.0	5.7	61	2.90	12200	4.0	4.88
24	0.20	6000	8.0	4.8	62	0.90	2600	1.0	0.26
25	0.50	8900	9.0	8.01	63	1.00	7400	8.0	5.92
26	0.50	8900	9.0	8.01	64	1.60	2600	2.0	0.52
27	0.20	14400	7.0	10.08	65	0.50	10400	4.0	4.16
28	3.20	13900	8.0	11.12	66	1.60	6900	3.0	2.07
29	1.30	4800	5.0	2.4	67	0.40	9200	8.0	7.36
30	0.50	7800	6.0	4.68	68	0.70	7400	6.0	4.44
31	0.20	11700	7.0	8.19	69	0.50	6900	1.0	0.69
32	0.60	14400	7.0	10.08	70	0.30	8700	7.0	6.09
33	0.60	12400	4.0	4.96	71	0.70	10500	3.0	3.15
34	0.60	15100	6.0	9.06	72	0.30	8700	7.0	6.09
35	0.30	7600	8.0	6.08	73	1.20	12000	3.0	3.6
36	1.10	12400	4.0	4.96	74	0.30	8400	4.0	3.36
37	0.60	11000	7.0	7.7	75	0.40	6900	8.0	5.52
38	1.90	11000	7.0	7.7	76	0.40	12000	7.0	8.4

Fortunately, hazmat transportation possesses a very low accident probability. Kokkinos et al. (2012) reported that the hazmat accident rate is about $10^{-6} \sim 10^{-8}$ per km traveled ($6.21 \times 10^{-7} \sim 6.21 \times 10^{-9}$ per mile). A small incident probability between 1×10^{-8} to 9×10^{-8} per mile was generated for all links assuming a uniform distribution within that range. The unit of risk, the product of population and accident rate, is person exposure per mile traveled.

The shortest paths for each origin-destination pair are calculated at the beginning of the algorithm without imposing any link restrictions on the network ($z_{ij} = 0$). These paths represent the second objective, without considering the first objective. The path cost in these paths are the lower bound of the cost in this bi-objective problem. These paths are the desirable hazmat routes when no restrictions are imposed to any link for safety purpose. The paths are reported as A1, B1, C1, and D1 for O-D pairs (2, 18), (2, 22), (3, 18), and (3, 22), respectively, in Table 2. Link 39 (node 13–node 24) possesses the greatest risk and is restricted at the first iteration. The risk value of link 39 is the upper bound of the risk in the bi-objective problem. The restriction on link 39 does not impact the travel decision for O-D pairs (2, 18) and (3, 18) because A1 and C1 do not utilize link 39. However, the desirable paths for O-D pairs (2, 22) and (3, 22) change because of this restriction. The new paths are shown as B2 and D2 with path costs 222 minutes and 240 minutes in Table 2. After closing 32 links, O-D pairs (3, 18) and (3, 22) become inaccessible, while O-D pairs (2, 18) and (2, 22) become inaccessible after closing 35 links, as shown in Table 2. We stop the algorithm after this since there are no routes available for any O-D pair. Figure 3 illustrates the reduction in link risk until no paths are available. The corresponding path costs due to closure of links are shown in Figure 4.

Figure 5 shows link risk vs. path cost for each O-D pair for all iterations. The figure shows the influence of the link closure on the desirable routing (shortest path) strategy. Each point in the plot represents a link risk that has been restricted and the shortest path due to this restriction. These points correspond to the solution (α_r, β_r) described in the algorithm. Paths on the same vertical line on the plots are not non-dominant, because the route selection strategy did not change even though the riskier links are being closed. For example, with O-D pair (2, 18), restricting the first eight links on the network does not change the shortest path. The path costs are therefore not dependent on the link restriction; furthermore, the risk and path cost combination during these iterations are not non-dominant.

The non-dominant solutions (α^0, β^0) can be identified from Figure 5 in addition to the algorithm. To identify a non-dominant (Pareto optimal) frontier, it is necessary to identify the risk level where the route selection strategy changes. If a new path is found for a particular link closure, the associated link risk and the cost of the previous path constitute a point of the Pareto frontier. There are only three paths (A1, B1, and C1) that are generated for O-D pair (2, 18). Newer (A1 to A2, A2 to A3) or inaccessible paths (infinite cost) are generated when closing links with risk 9.84, 8.01, and 6.37, respectively. The non-dominant points for O-D pair (2, 18) are the risk and cost combination of (link 20, path A1), (link 25, path A2), and (link 30, path A3). Figure 6 shows the Pareto solutions for the four O-D pairs. The paths represented by each point are shown in Table 2.

The non-dominant solutions have important implications for decision making, both from regulators' and shipper/carriers' perspectives. Figure 6 summarizes the travel cost imposed on shipper/carriers when a particular hazmat link prohibition strategy is implemented. Furthermore, for a particular risk value, the paths below that risk value are those available for hazmat transport. For example, if the regulator's target is to restrict all links with risk greater than or equal to 10, all paths are available to shipper/carriers for O-D pair (2, 18) because the risk on all relevant paths lies below this threshold. The shipper/carriers will most likely choose path A1 because it gives the lowest cost among all paths. If they are more concerned about risk, they may choose either A2 or A3 if cost is not a major issue. For all other O-D pairs, they lose their first choices B1, C1, and D1 and may choose second lowest cost paths B2, C2, and D2. Observing the non-dominated front for O-D pair (2, 22) explains that some cases may occur when risk may be reduced even without visibly increasing cost. If the first routing strategy (route B1) is eliminated and the second option (route

Table 2: Path Selections at Each Link Closure

Number of Link Closure	Link ID	Link Risk§ (×10⁻⁴)	OD Pair (2,18)		OD Pair (2,22)		OD Pair (3,18)		OD Pair (3,22)	
			Shortest Path*	Path Cost (min)	Shortest Path*	Path Cost (min)	Shortest Path*	Path Cost (min)	Shortest Path*	Path Cost (min)
0	N/A	N/A	2-6-8-7-18 (A1)	144	2-2-3-12-13-24-23-22 (B1)	216	3-12-11-10-17-16-18 (C1)	186	3-12-13-24-23- 22 (D1)	138
1	39	16.56	2-6-8-7-18 (A1)	144	2-6-8-7-18-20-22 (B2)	222	3-12-11-10-17-16-18 (C1)	186	3-12-11-14-15-22 (D2)	240
2-5	6,28,27,32	11.97-10.08	2-6-8-7-18 (A1)	144	2-6-8-7-18-20-22 (B2)	222	3-12-11-4-5-9-8-7-18 (C2)	276	3-12-11-14-15-22 (D2)	240
6-11	12,15,17,20,53,58	9.99-9.84	2-6-8-9-10-17-16-18 (A2)	288	2-2-3-12-11-14-15-22 (B3)	318	3-12-11- 4-5- 9-10-17-16-18-20 (C3)	306	3-12-11-14-15-22 (D2)	240
12-13	41,44	9.44	2-6-8-9-10-17-16-18 (A2)	288	2-6- 8-9-10-17-16-18-20-22 (B4)	366	3-12-11- 4-5- 9-10-17-16-18-20 (C3)	306	3-12-11-14-23-22 (C4)	300
14-15	40,34	9.06	-2-6-8-9-10-17-16-18 (A2)--	288	2-6- 8-9-10-17-16-18-20-22 (B4)	366	3-12-11- 4-5- 9-10-17-16-18-20 (C3)	306	3-12-11-4 -5-9-10-17 -16-18-20-22 (D4)	384
16-19	60,11,76,31	8.64 -8.19	2-6-8-9-10-17-16-18 (A2)	288	2-6- 8-9-10-17-16-18-20-22 (B4)	366	3-3-2- 6-8-9-10-17-16-18 (C4)	504	3-1- 2-6-8-9-10-17-16-18-20-22 (D5)	582
20	25	8.01	2-6-8-16-18 (A3)	306	2- 6-8-16-18-20-22 (B5)	384	3-3-2-6-8-16-18 (E5)	522	3-1-2-6-8-16-18-20-22 (D6)	600
21-32	26,8,45,57,49,52,37,38,46,67,2,5	8.01-7.2	2-6-8-16-18 (A3)	306	2- 6-8-16-18-20-22 (B5)	384	Inaccessible	Inf	Inaccessible	Inf
33-35	13,55,50	6.65-6.37	Inaccessible	Inf	Inaccessible	Inf				

§ Link risk are reported in decreasing order
* Shortest paths are reported as node-to-node

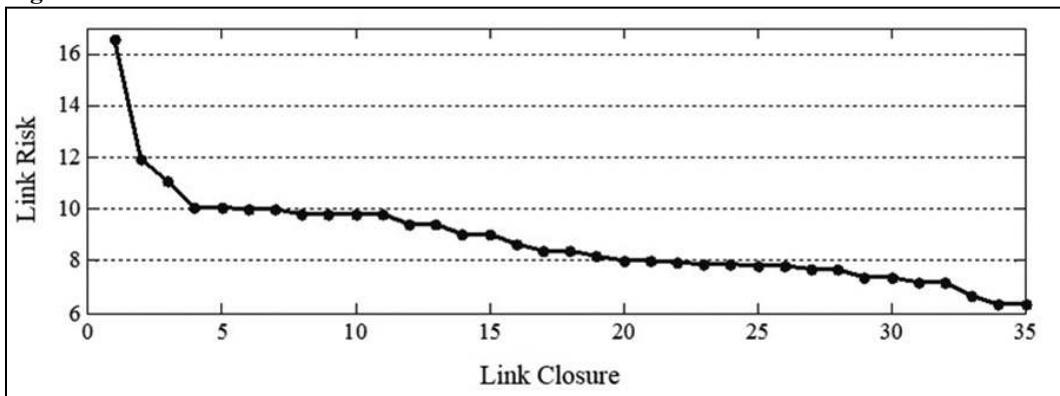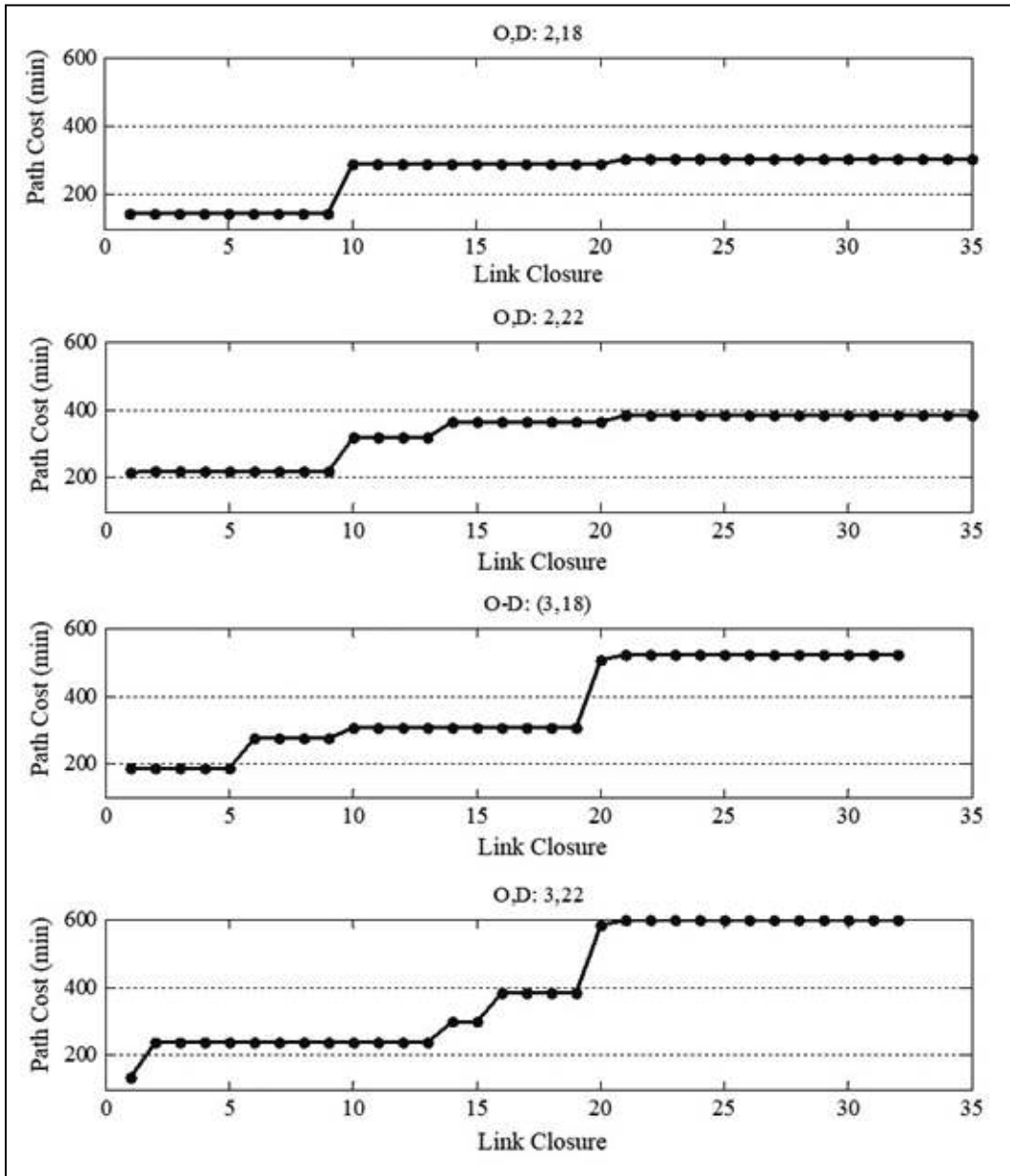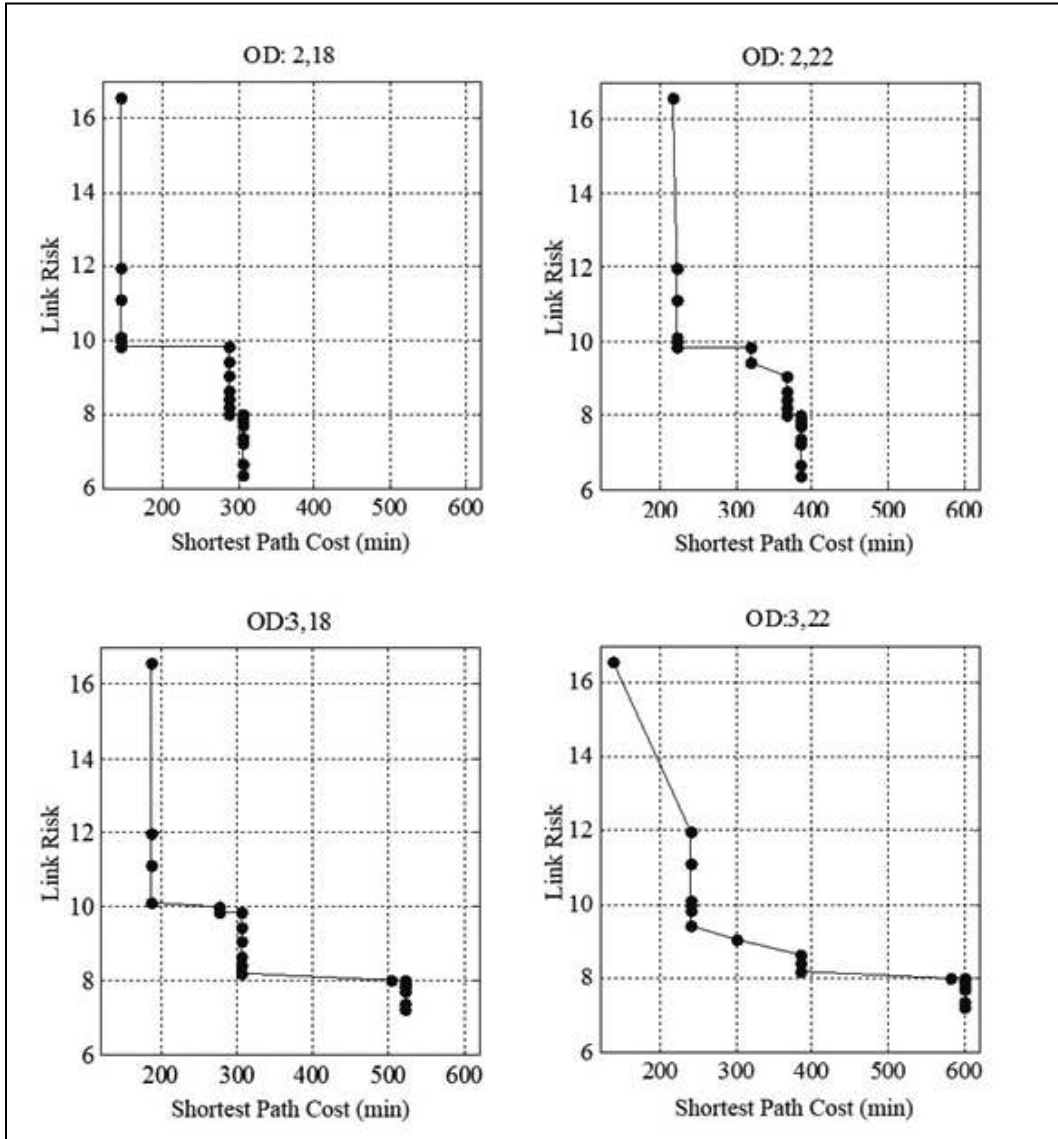**Figure 3: Link Risk at Each Link Closure**

Figure 4: Cost vs. Link Closure for Each O-D Pair

B2) is taken, we can reduce risk 40% (16.56 to 9.84) with only about a 3% (216 min to 222 min) increase in travel cost. It is seen that a substantial increase is observed for O-D pair (3, 18) and (3, 22) if first routing options are eliminated. The costs for O-D pair (3, 18), and (3, 22) increase to 48.39% (186 min, path C1 to 276 min, route C2), and 73.91% (138 min, path D1 to 240 min, route D2), respectively. The risk reduction for O-D pair (3, 18) is only 2.5%, however, for O-D pair (3, 22), it is about 42%.

In addition to a Pareto optimal front for each of the O-D pairs, a system level Pareto frontier can serve regulators in evaluating the trade-off between link closure and system level cost. The
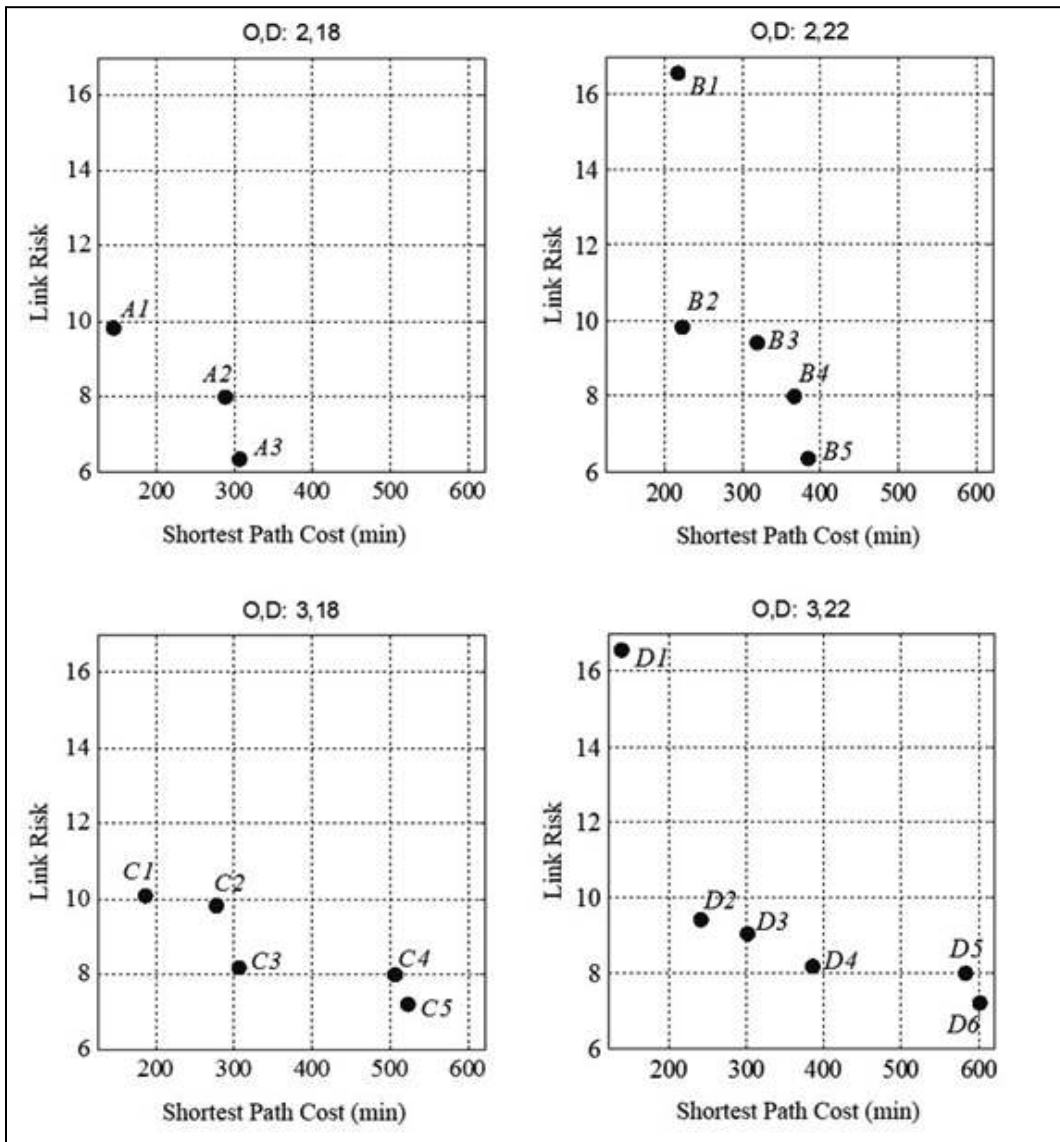
Figure 5: Link Risk vs. Path Cost

system-level Pareto points are constructed by summing the path costs of all shortest paths at a given restricted network and the associated maximum link risk as shown in Figure 7. It is seen that if the allowable maximum risk is set to 10, the system cost increases from 684 min, when there is no restriction, to 882 min. Also, the allowable maximum risk cannot be lowered below 7.2 because no paths will be available for any shipments.

The bi-objective model discussed in this paper can offer insights to identify a risk threshold value for regulators and to determine how route choice may be affected by such restrictions. For shippers and carriers, this will provide a strategy to verify the suitability of routing, how to decrease transportation costs, and if risk is being shifted from one subpopulation to another. Although the analysis was demonstrated with a hypothetical network, the model can be used for any network with real data.
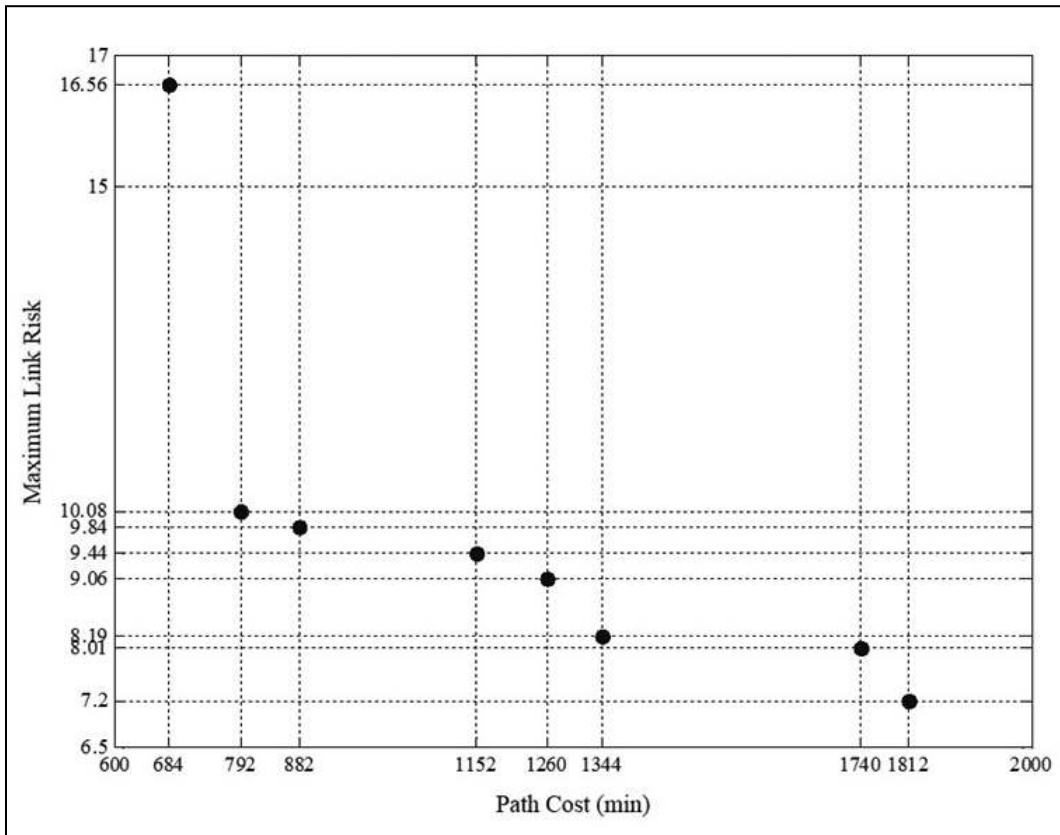
Figure 6: Pareto Optimal Frontiers for Each O-D Pair

CONCLUDING REMARKS

A bi-objective shortest path problem was formulated for hazardous materials routing. Although the method was applied to a test network, the methods can be applied to any network as a decision-support tool for hazmat link prohibition policies. The method described in this paper constructs non-dominated frontiers for each origin-destination pair and the complete hazmat transportation network, which can aid a regulatory agency to establish and evaluate a tolerable threshold risk; the links exceeding the risk tolerance may then be restricted, and routing plans minimizing the impact on the carriers can be identified. Shippers and carriers can also establish their routing strategies by eliminating paths that utilize high risk links to determine an appropriate cost estimate of transportation. The method described in this paper can therefore be used to compare alternative regulation and routing strategies to achieve a desired balance between risk and routing convenience.

Figure 7: System Level Pareto Optimal Frontier

In future research, these metrics will be illustrated on medium- and large-scale real transportation networks considering multi-commodity hazmat flow.

The model is static, not dynamic, so it doesn't include travel time variability by day of the week or by season of the year. The model also doesn't identify the effect that weather has on dispersal areas of hazardous materials. These matters are outside the scope of the paper, which is focused on hazmat routing. Thus, the paper doesn't consider accident risk during loading and unloading.

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Disclaimer

The views and conclusions contained in this document are those of the authors and should not be interpreted as necessarily representing the official policies, either expressed or implied, of the U.S. Department of Homeland Security.

References

Bell, M.G.H. "Mixed Route Strategies for the Risk-Averse Shipment of Hazardous Materials." *Networks and Spatial Economics* 6 (3), (2006): 253-265.

Bell, M.G.H. "Mixed Routing Strategies for Hazardous Materials: Decision-Making Under Complete Uncertainty." *International Journal of Sustainable Transportation* 1 (2), (2007): 133-142.

Berman, O., D. Einav, and G. Handler. "The Constrained Bottleneck Problem in Networks." *Operations Research* 38 (1), (1990): 178-181.

Bianco, L., M. Caramia, and S. Giordani. "A Bilevel Flow Model for Hazmat Transportation Network Design." *Transportation Research Part C: Emerging Technologies* 17 (2), (2009): 175-196.

Chang, T.S., L.K. Nozick, and M.A. Turnquist. "Multiobjective Path Finding in Stochastic Dynamic Networks, with Application to Routing Hazardous Materials Shipments." *Transportation Science* 39 (3), (2005): 383-399.

Dadkar, Y., L. Nozick, and D. Jones. "Optimizing Facility Use Restrictions for the Movement of Hazardous Materials." *Transportation Research Part B: Methodological* 44 (2), (2010): 267-281.

de Lima Pinto, L., C.T. Bornstein, and N. Maculan. "The Tricriterion Shortest Path Problem with at Least Two Bottleneck Objective Functions." *European Journal of Operational Research* 198 (2), (2009): 387-391.

Erkut, E. and F. Gzara. "Solving the Hazmat Transport Network Design Problem." *Computers & Operations Research* 35 (7), (2008): 2234-2247.

Erkut, E. and A. Ingolfsson. "Catastrophe Avoidance Models for Hazardous Materials Route Planning." *Transportation Science* 34 (2), (2000): 165-179.

Erkut, E. and V. Verter. "Modeling of Transport Risk for Hazardous Materials." *Operations Research* 46 (5), (1998): 625-642.

Hollander, Y. and J.N. Prashker. "The Applicability of Non-Cooperative Game Theory in Transport Analysis." *Transportation* 33 (5), (2006): 481-496.

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

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

Kokkinos, K., E. Papadopoulos, N. Samaras, and K. Chaikalis. "An Integrated Modeling Framework for Routing of Hazardous Materials." In *IEEE 21st International Workshop on Enabling Technologies: Infrastructure for Collaborative Enterprises (WETICE),* (2012): 226-231.

List, G. and P. Mirchandani. "An Integrated Network/Planar Multiobjective Model for Routing and Siting for Hazardous Materials and Wastes." *Transportation Science* 25 (2), (1991): 146-156.

List, G.F., P.B. Mirchandani, M.A. Turnquist, and K.G. Zografos. "Modeling and Analysis for Hazardous Materials Transportation: Risk Analysis, Routing/Scheduling and Facility Location." *Transportation Science* 25 (2), (1991): 100-114.

Lownes, N.E., Q. Wang, S. Ibrahim, R.A. Ammar, S. Rajasekaran, and D. Sharma. "Many-to-Many Game-Theoretic Approach for the Measurement of Transportation Network Vulnerability." *Transportation Research Record: Journal of the Transportation Research Board* 2263 (1), (2011): 1-8.

Miller-Hooks, E. and H.S. Mahmassani. "Optimal Routing of Hazardous Materials in Stochastic, Time-Varying Transportation Networks." *Transportation Research Record: Journal of the Transportation Research Board* 1645 (1), (1998): 143-151.

Nozick, L.K., G.F. List, and M.A. Turnquist. "Integrated Routing and Scheduling in Hazardous Materials Transportation." *Transportation Science* 31 (3), (1997): 200-215.

Nune, R. and P. Murray-Tuite. "Comparision of Potential Paths Selected by a Malicious Entity with Hazardous Materials: Minimization of Time vs. Minimization of Distance." In *IEEE Winter Simulation Conference*, (2007): 1161-1167.

Rahman, A., N.E. Lownes, J.N. Ivan, L. Fiondella, S. Rajasekaran, and R. Ammar. "A Game Theory Approach to Identify Alternative Regulatory Frameworks for Hazardous Materials Routing." In *IEEE Homeland Security Conference (HST)*, (2012): 489-494.

Reilly, A., L. Nozick, N. Xu, and D. Jones. "Game Theory-Based Identification of Facility Use Restrictions for the Movement of Hazardous Materials Under Terrorist Threat." *Transportation Research Part E: Logistics and Transportation Review* 48 (1), (2012): 115-131.

Shaver, D.K. and M. Kaiser. *Criteria for Highway Routing of Hazardous Materials*. Washington, D.C.: Transportation Research Board, 1998.

U.S. Department of Transportation. *2007 Economic Cencus: 2007 Commodity Flow Survey*, July 2010.

Ukkusuri, S.V. and W.F. Yushimito. "A Methodology to Assess the Criticality of Highway Transportation Networks." *Journal of Transportation Security* 2 (1), (2009): 29-46.

U.S. Department of Transportation. *Guidelines for Applying Criteria to Designate Routes for Transporting Hazardous Materials*. Washington D.C.: Federal Highway Administration, 1994.

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