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A Tactical Planning Model for Railroad Transportation of Dangerous Goods

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Abstract. Railroad transportation of hazardous materials did not receive as much attention as highway transportation in the academic literature, although comparable volumes are shipped via these two transport modes in North America and Europe. In this paper we present an optimization methodology for the railroad tactical planning problem with risk and cost objectives. We determine the routes to be utilized for each shipment, the yard activities, and the number of trains of different types needed in the network. The transport risk assessment component of our model incorporates the differentiating characteristics of railroad operations. We develop a Memetic Algorithm based solution methodology, which combines genetic and local searches, to solve the bi-objective model. The railroad infrastructure in Midwest US is used as a basis for generating problem instances of the size encountered in real life. Our analyses of the solutions of instances indicate that it is possible to achieve significant reductions in population exposure without incurring unacceptable increases in operational costs.

Keywords. Railroad transportation, dangerous goods, Gaussian plume model, multi-criteria model, memetic algorithm.

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INTRODUCTION

Hazardous materials (hazmat) are harmful to the humans and the environment due to their toxic ingredients, but their transportation is essential to sustain our industrial life-style. A significant majority of hazmat shipments are moved via the highway and railroad networks. In Canada, for example, 92% of hazmat shipments are moved by trucks and trains, and the amounts shipped via the two modes are 64 million tons and 48 million tons, respectively (Transport Canada, 2002-03). On the other hand, in US, around 140 million tons of hazmat was moved by railroads in 2007 (US Department of Transportation, 2007). The quantity of hazmat traffic on railroad networks is expected to increase significantly over the next decade, given the phenomenal growth of intermodal transportation and the growing use of rail-truck combination to move chemicals. Fortunately a host of industry-wide initiatives and the implementation of a comprehensive safety plan of the Federal Railroad Administration (FRA) make railroads one of the safest modes to transport hazmat (Federal Railroad Administration, 2008). Although less than 1% of hazmat incidents in US resulted from railroads, consistent with the worldwide statistic presented in Oggero et al. (2006), the possibility of spectacular events resulting from multi railcar incidents, however small, do exist. The derailment of the BNSF train in Lafayette (US), spilling 10,000 gallons of hydrochloric acid and forcing more than 3000 residents out of their homes, is an example of such low probability –high consequence events (Insurance Journal, 2008).

It was interesting to note that although roads and railroad are equally important means of moving hazmat, an overwhelming majority of the research on hazmat transportation focuses on road shipments (Erkut et al., 2007). The sparse literature on railroad transportation of hazmat mainly deals with analyzing past accident data in an effort to increase railroad safety by improving rail tracks or rail-car tank designs. The distinguishing characteristics of rail shipments are not incorporated in this body of literature, which we review in the next section. Verma and Verter (2007) point out that trains can have multiple sources of (hazmat) release in the event of a multiple-railcar incident, whereas trucks constitute a single release-source. Furthermore, the volume of the potentially hazardous freight varies in trains, whereas trucks carry a constant volume of a given hazmat type. Clearly, these differences have implications in terms of the exposure (or impact) zone around a train.

We focus on the *tactical planning problem* of a railroad company that regularly transports a predetermined amount of mixed freight (i.e., non-hazardous and hazardous cargo) across a railroad network. In the context of regular freight, this problem has been first described by Assad (1980a) and analyzed in detail by Crainic et al. (1984). It is interesting to note that the tactical planning problem that also involves hazardous cargo has not been studied during the more than two decades that passed since the seminal works, mentioned above. Given the increasing volume of hazardous cargo shipped via railroads, our work is motivated by the crucial need to develop an analytical approach to incorporate the transport risks associated with hazardous cargo in the tactical planning decisions. Consequently, the solution to the mixed-freight tactical planning problem we study in this paper comprises: (i) the number and make-up of trains of each service type; and (ii) the routing (i.e., train service itinerary) for each shipment that minimize the transport cost and the transport risk. We propose a bi-objective optimization framework to address the interests of the primary stakeholders i.e., regulatory agencies and railroad companies. Tactical planning has been among the routine tasks of the managers at railroad companies for a long time, and involves decisions on effective resource allocation. The common practice among managers, however, has been to plan line and yard operations with an objective to minimize system-wide costs (Assad, 1980a). Considering the increased environmental awareness among government officials and public at large, the railroad companies are under increasing pressure to also consider the public and environmental risks associated with their activities. This paper constitutes the first attempt in the academic literature to develop an analytical framework that incorporates both operational costs and transport risks to help managers develop comprehensive tactical plans. Our computational experiments on realistic problem instances indicate that it is possible to achieve significant reductions in population exposure without incurring unacceptable increases in operational costs.

The remainder of the paper is organized as follows: Section 1 provides an overview of the three most relevant streams of literature and underlines that existing academic literature does not provide any help with the tactical planning of railroad shipments of hazmat. Section 2 defines the problem of interest, while Section 3 presents a bi-objective model that aims at minimizing both the transport cost and risk across a railroad network. Section 4 presents a Memetic Algorithm (MA) based solution methodology. MA, a hybrid meta-heuristic technique, combines the attributes of genetic and local searches to solve large scale optimization problems. Section 5 makes use of the railroad infrastructure in Midwest US for generating problem instances of the size encountered in real life, which are then solved using the proposed methodology. This section also reports on the algorithm performance, and a number of managerial insights on the tactical planning problem. We conclude the paper with some final remarks in Section 6.

1. LITERATURE REVIEW

In this section, we review the most relevant streams of research. These bodies of literature include the papers that focus on: the routing problems arising in railroad transportation; the railroad shipments of hazmat; and, the transport risk assessment models for hazmat that are airborne upon release from a container.

The early papers on railroad *routing* and scheduling mainly propose the use of simulation (Assad, 1980b; Haghani, 1987). This area of research is rather developed and we invite the reader to refer to Cordeau et al. (1998) for a comprehensive survey of the literature prior to mid-90s.

The second stream of research can be grouped under *transportation of hazmat* and *tank car design*. Railroad transportation of hazmat has been studied by a number of academic and industry researchers. Analyzing past data on train derailments, Glickman and Rosenfield (1984) derived and evaluated three forms of risk: the probability distribution of the number of fatalities in a single accident, the probability distribution of the total number of fatalities from all the accidents in a year, and the frequency of accidents that result in any given number of fatalities. Glickman (1983) showed that rerouting of trains with (or without) track upgrades can reduce risk. The trade-off between the societal and individual risks of hazmat shipments is addressed in Saccomanno and Shortreed (1983). Barkan et al. (2003) concluded that the speed of derailment and the number of derailed cars are highly correlated with hazmat release, and most recently, Kawprasert and Barkan (2008) proposed a route rationalization approach to reduce rail risk.

The railroad industry has spent considerable effort in reducing the frequency of tank car accidents as well as the likelihood of releases in the event of an accident. To this end, the Association of American Railroads, Chemical Manufacturers Association, and Railway Progress Institute formed an inter-industry task force in the early 1970's (Conlon, 1999). Unfortunately, the activities of this voluntary task force largely ceased in about 1994, and most of their internal reports were never published and are proprietary to the sponsoring organizations (Barkan, 2004; Conlon, 2004). More recent industry initiatives, such as Raj and Pritchard (2000), Barkan et al. (2000, 2007), and Saat and Barkan (2005), have focused on improving the tank car safety at the design stage.

The last stream of research deals with the use of *air dispersion models* for assessing transport risk, since we adopt a conservative approach by focusing on hazmat that are airborne on (accidental) release. Note that the exposure zone for such hazmat e.g., chlorine, ammonia, PCB wastes burning in low-fire, is much larger than for non-airborne materials. This is because the resulting toxic fumes (or clouds) can travel long distances under windy weather conditions. The most common analytical approach for assessing the accident risk in such cases has been the use of *dispersion* models.

The Gaussian plume model (GPM), which we use in this paper, is by far the most popular dispersion model used by micro-meteorologists, air pollution analysts, and regulatory agencies (Gifford, 1975). GPM models have received “official blessing” from state and federal regulatory agencies in the U.S., and their use has been recommended in official regulatory guidelines (Arya, 1999). Patel and Horowitz (1990) were the first to use GPM, coupled with a geographical information system (GIS), for risk assessment of road shipments. Recently, Zhang et al. (2000) modeled the probability of an undesirable consequence as a function of the concentration level through a GPM model. On the other hand, the application of dense-gas dispersion model and Lagrangian-integral dispersion model can be seen in Leeming and Saccomanno (1994) and Hwang et al. (2001), respectively.

2. PROBLEM DESCRIPTION

In a railroad transportation system, the physical infrastructure comprises of rail-yards and tracks. Some of the yards are fully-equipped, i.e., both classification and transfer operations are possible, while others can only perform block-swap (transfer) operations. Any two nodes are connected by tracks, which are the *service-legs* of a train traveling non-stop between them. A sequence of service-legs and intermediate yards constitutes an *itinerary* available to a railcar for its journey.

For major freight railroads, demand is expressed as a set of individual railcars that share a common origin and destination yard. To prevent railcars from being handled at every intermediate yard, railroads group several railcars together to form a *block* (Kuehn, 2005). A block is associated with an origin-destination pair that may or may not be the origin or destination of the railcars contained in the block. The sequence of blocks to which a railcar is assigned on its journey from the origin to the destination yard is called a *blocking path* (Newton et al., 1998; Barnhart et al., 2000).

We characterize demand (or traffic class) by unique origin and destination yards, and the type of cargo i.e., hazardous or non-hazardous. We extend the concept of an itinerary to include not only the service-legs and intermediate yards a railcar traverses, but also the blocking-path it is assigned. So, the tactical planning problem is to determine the number and make-up of each type of train service, and the itineraries for each shipment such that the transport cost and the transport risk are minimized for the given set of demand for mixed freight.

3. MODEL DEVELOPMENT

3.1 The Model

Following the prevailing literature on hazmat transportation, we propose a bi-objective optimization model that is intended to address the interests of two stakeholders i.e., the regulatory agencies and the railroad companies. We use *population exposure* (i.e., the total number of people exposed to the possibility of suffering the undesirable consequences of an incident) as the measure of transport risk. For example, according to the North American Emergency Response Handbook (ERG, 2008), 800m around a fire that involves a chlorine tank, railcar or tank-truck must be isolated and evacuated, and hence people within this predefined threshold distance are exposed to the risk of evacuation. The fixed bandwidth approach was first suggested by Batta and Chiu (1988) and ReVelle et al. (1991), and has been used by many authors since then. In Verma and Verter (2007), we showed that the use of a fixed bandwidth is not suitable for trains since it assumes a fixed volume of hazardous cargo on board. As a result, we developed a model that estimated exposure zone as a function of volume (and type) of hazmat on the train, and where a population center was exposed if the aggregate concentrate level exceeded the immediately dangerous to life and health (IDLH) level specified for the hazmat being shipped. The perspective of the railroad company is taken into consideration via transport cost. Although bi-objective *'cost-risk'* models have been studied in the context of highway shipments (Erkut and Verter, 1995; List et al., 1991), nothing similar exists for railroad transportation (Erkut et al., 2007).

In developing the mathematical formulation, we make three assumptions. *First*, tactical planning is conducted on a weekly basis and hence the demand is expressed in terms of number of railcars to be shipped per week. *Second*, the details at the operational level, such as the impact of traffic congestion and connections between train services, are out of the scope of our tactical planning model and hence ignored. This amounts to assuming that all the railcars to be moved are available at their origin at the beginning of the week. *Third*, all the hazmat being shipped on a train possess similar chemical properties and the undesirable consequences of their interactions in the event of an incident can be ignored. It is important to note that, to the best of our knowledge, there is no peer-reviewed publication demonstrating the interaction effects among prevalent types of hazmat. Now we turn to the development of our model.

Sets and Indices

L: Set of train services, indexed by *l*.

S_l: Set of service legs for train service *l*, indexed by *s*.

C: Set of classification yards, indexed by *c*.

T: Set of transfer yards, indexed by *t*.

M: Set of demands, indexed by *m*.

I^m: Set of itineraries for demand *m*, indexed by *i*.

$I_{l,s}$: Set of itineraries that use service leg *s* of train service *l*.

I_l: Set of itineraries using train service *l*.

I_c: Set of itineraries using classification yard *c*.

I_t: Set of itineraries using transfer yard *t*.

I_y: Set of itineraries using yard $y \in C \cup T$.

Decision Variables

$$X_i^m = \begin{cases} 1, \text{ if demand } m \text{ is met using itinerary } i, \\ 0, \text{ otherwise.} \end{cases}$$

$N_l =$ Number of trains that provide service *l*.

$Y_{l,s} =$ Number of hazmat railcars on service leg *s* of train service *l*.

$Y_y =$ Number of hazmat railcars using yard *y*.

Parameters

$E(Y_{l,s}) =$ Cumulative exposure resulting from decision $Y_{l,s}$.

$E(Y_y) =$ Cumulative exposure resulting from decision Y_y.

$C_i^m =$ Operating cost per railcar of demand *m* on itinerary *i*.

$C_l =$ Operating cost of a train that provides service *l*.

$h^m =$ Number of hazmat railcars in demand *m*.

$\overline{h}^m =$ Number of non-hazmat railcars in demand *m*.

$U_l =$ Maximum number of railcars on a train that provides service *l*.

$K_c =$ Number of railcars that can be classified per week at yard *c*.

$K_t =$ Number of railcars that can be transferred per week at yard *t*.

(P)

$$Minimize \qquad Exposure = \sum_{l \in L} \sum_{s \in S_l \cap I_{l,s}} E(Y_{l,s}) + \sum_{y \in C \cup T} E(Y_y)$$
$$Cost = \sum_{m \in M} \sum_{i \in I^m} C_i^m X_i^m (h^m + \bar{h}^m) + \sum_{l \in L} C_l N_l \qquad (1)$$

s.t.:

$$\sum_{i \in I^m} X_i^m = 1 \qquad \forall m \in M \qquad (2)$$

$$\sum_{m \in M} \sum_{i \in I^m \cap I_l} X_i^m (h^m + \bar{h}^m) \le U_l N_l \qquad \forall l \in L \qquad (3)$$

$$\sum_{m \in M} \sum_{i \in I^m \cap I_c} X_i^m (h^m + \bar{h}^m) \le K_c \qquad \forall c \in C \qquad (4)$$

$$\sum_{m \in M} \sum_{i \in I^m \cap I_t} X_i^m (h^m + \bar{h}^m) \le K_t \qquad \forall t \in T \qquad (5)$$

$$\sum_{m \in M} \sum_{i \in I_{l,s}} X_i^m h^m = Y_{l,s} \qquad \forall s \in S_l, \forall l \in L \qquad (6)$$

$$\sum_{m \in M} \sum_{i \in I_y} X_i^m h^m = Y_y \qquad \forall y \in C \cup T \qquad (7)$$

$$X_i^m \in \{0,1\} \qquad \forall m \in M, \forall i \in I^m \qquad (8)$$

$$Y_{l,s} \ge 0 \ \ integer \qquad \forall l \in L, \forall s \in S_l \qquad (9)$$

$$Y_y \ge 0 \ \ integer \qquad \forall y \in C \cup T \qquad (10)$$

$$N_l \ge 0 \ integer \qquad \forall l \in L \qquad (11)$$

The first objective in (1) contains population exposure on *lines* and at *yards* in the rail network. The exposure estimates are based on only the hazmat railcars and capture the *economies of risk* that exists when more than one railcar with hazmat cargo are moving together (Verma and Verter, 2007). The population exposure for a particular service leg (or at a yard) of a train service is a function of the total number of hazmat railcars involved, which is not known a priori. We elaborate further on this in subsection 3.2. The second objective in (1) contains railcar routing cost and the fixed cost to provide a given type of train service.

Constraint (2) stipulates that the weekly demand for each traffic class will be met using exactly one of the available itineraries for each traffic class i.e., demand will not be split. This is desirable from the standpoint of moving hazmat railcars, since grouping them will yield economies of risk. This is also desirable from the cost perspective since it implies that a single group of railcars will be formed for every demand (origin-destination pair), which is in line with the policy of railroads to minimize intermediate handling. Constraint (3) determines the number of trains of each type required to meet the given demand. Constraints (4) and (5) enforce the classification and transfer capacities of the yards. Constraints (6) and (7), respectively, determine the number of hazmat railcars that are using any service leg of a particular train type or being serviced at a yard. Finally constraints (8) – (11) specify sign restrictions on the variables.

3.2 Parameter Estimation

Some costs are based on the work of Ahuja et al. (2007), and hence a \$0.50 cost to move a railcar one mile and \$50 per intermediate handling is assumed. The fixed cost of the train is based on the number of hours it takes to provide a service, and an hourly rate of \$100 is assumed. Finally, it is assumed that the average speed of freight train in the US is around 30 miles per hour (Railroad Performance Measures, 2008).

As indicated earlier, we use population exposure as the measure of transport risk. As explained in Verma and Verter (2007), a population center is exposed if the aggregate concentrate level exceeds the critical (IDLH) level for the hazmat being shipped. To make this explicit, consider that *n* hazmat railcars are using service leg *s* of train type *l*. By making use of GPM, and the methodology developed in Verma and Verter (2007), the aggregate concentrate level at downwind distance *x* can be determined as:

$$\overline{C}_n(x) = \frac{Q}{\pi\, u\, a\, c\, x^b\, x^d} \times n \tag{12}$$

where Q is the release rate; u is the wind speed; a, b, c and d are atmospheric constants; and, x is the downwind distance from the *hazmat-median* (center of the hazmat railcar block) of the train. At an IDLH level of $\tilde{C}$, the threshold distance can be determined using (13).

$$\tilde{x} = \sqrt[b+d]{\frac{n \times Q}{\pi\, u\, a\, c\, \tilde{C}}} \times n \tag{13}$$

The movement of the danger circle, of radius $\tilde{x}$, along a link will carve out a band, and the number of people within the band is the *population exposure* due to the release from *n* hazmat railcars. For example, transport risk due to hazmat release of volume $Y_{l,s}$ on service leg *s* of train type *l* can be calculated by:

$$E(Y_{l,s}) = \tilde{x}(Y_{l,s}) \times \text{ length of service leg } s \times \rho(\tilde{x}(Y_{l,s})) \tag{14}$$

where ρ is the population density of the center exposed due to the transportation of hazmat on service leg s. The population centers exposed depends on the threshold distance, which in turn depends on the hazmat volume being transported on a particular service leg. It is clear from (14) that the function for calculating population exposure is non-linear with a rather complicated form, and without a closed form expression. It is important to note that a priori determination of population exposure risk, for every service leg and at every yard, for even a small problem instance will require a lot of preprocessing effort and time. It is because a singular risk calculation instance entails using (12) - (14), and avenue programming in ArcView GIS (ARC VIEW, 1996); and this has to be done for every possible number of hazmat railcars at various points in the network.

4. SOLUTION METHODOLOGY

In the absence of a closed-form expression for the risk objective in **(P)**, solving realistic size problem instances through the use of general purpose optimization software would be rather inefficient. But since **(P)** typically contains a huge number of variables and relatively fewer constraints, a Genetic Algorithm (GA) based solution methodology would be more effective and efficient (Holland, 1975). We replace the traditional mutation operator in GA with a local search heuristic, which will ensure a more effective neighborhood search (i.e., intensification). Consequently, our solution methodology for **(P)** is a *Memetic Algorithm* (MA) that combines global and local searches (Moscato, 1989). We first outline the main components of our solution approach and then provide a formal statement of the MA in figure 1.

In GA, a proposed solution is defined as a set of values represented as a simple string called a chromosome (also genome). Given the nature of our problem, we determine the length of the chromosome by the number of demand (traffic-classes), and use a non-binary encoding scheme. The non-binary encoding enables us to explicitly list the itinerary number being used to meet a particular demand. For example, the chromosome [2, 1, 5,….] indicates that the *first* demand is being met by moving railcars on the *second* itinerary, and so on. It should be noted that since the length of the chromosome (i.e., the number of available positions) ensures adherence to the demand constraints, MA will need to just evaluate the three capacity constraints (3)-(5).

It is possible to decompose **(P)** into a Cost Sub-Problem (P1) and an Exposure Sub-Problem (P2) as follows:

Cost Sub-Problem (P1)

$$Min\sum_{m\in M}\sum_{i\in I^m}C_i^m X_i^m(h^m+\bar{h}^m)+\sum_{l\in L}C_l N_l \quad (1')$$

s.t.:

$$\sum_{i\in I^m}X_i^m=1 \qquad \forall m\in M \quad (2')$$

$$\sum_{m\in M}\sum_{i\in I^m\cap I_l}X_i^m(h^m+\bar{h}^m)\le U_l N_l \quad \forall l\in L \quad (3')$$

$$\sum_{m\in M}\sum_{i\in I^m\cap I_c}X_i^m(h^m+\bar{h}^m)\le K_c \qquad \forall c\in C \quad (4')$$

$$\sum_{m\in M}\sum_{i\in I^m\cap I_t}X_i^m(h^m+\bar{h}^m)\le K_t \qquad \forall t\in T \quad (5')$$

$$X_i^m\in\{0,1\} \qquad \forall m\in M,\forall i\in I^m \quad (8')$$

$$N_l\ge 0; integer \qquad \forall l\in L \quad (11')$$

Exposure Sub-Problem (P2)

$$Min\sum_{l\in L}\sum_{s\in S_l\cap I_{l,s}}E(Y_{l,s})+\sum_{y\in C\cup T}E(Y_y) \quad (1'')$$

s.t.:

$$\sum_{m\in M}\sum_{i\in I_{l,s}}X_i^m h^m=Y_{l,s} \quad \forall s\in S_l,\forall l\in L \quad (6'')$$

$$\sum_{m\in M}\sum_{i\in I_y}X_i^m h^m=Y_y \quad \forall y\in C\cup T \quad (7'')$$

$$X_i^m\in\{0,1\} \qquad \forall m\in M,\forall i\in I^m \quad (8'')$$

$$Y_{l,s}\ge 0\ INT \qquad \forall s\in S_l,\forall l\in L \quad (9'')$$

$$Y_y\ge 0\ INT \qquad \forall y\in C\cup T \quad (10'')$$

Note that (P1) can be solved via a general purpose solver to determine the minimum cost solution.

Demand	***j***	***k***	***L***	**..**	**..**	**..**	***q-2***	***q-1***	***Q***
Mask	1	1	0	..	..	..	1	0	1
Itinerary	X_2^j	X_4^k	X_5^l	..	..	..	X_5^{q-2}	X_1^{q-1}	X_3^q

Table 1: Encoding and Mask Generation

A set of initial solutions is required to start GA. The first member is the *minimum cost* solution obtained by solving (P1) using a general purpose optimization package. Other members of the pool are generated by a double-randomization process. A 0-1 *mask* (string) of size *q* –same as the number of demand –is randomly generated (table 1). A value of *1* implies pre-assignment of the corresponding demand to one of the available itineraries, to be generated randomly, whereas *0* implies no pre-assignment. For example in table 1, k^{th} -demand is pre-assigned to the fourth itinerary (i.e., $X_4^k = 1$) for moving railcars between the origin-destination yard. Such pre-assignments are added to (P1) as additional (hard) constraints, which is then solved to generate other members of the pool.

Given the bi-objective formulation of **(P)**, the fitness of each chromosome (solution) will be a function of both cost and risk. While (P1) determines transport cost, the associated transport risk can be *assessed* using (6”) and (7”) via (P2). We aggregate the cost and risk attributes for each solution as per the preferences of the decision maker (i.e., the relative weights assigned to cost and risk). The resulting weighted objective values are used for ranking solutions in the pool. Clearly, modifying the weights alters the way in which the MA explores the solution space, which will become evident from our computational experiments reported in Section 5.

A *rank-based* roulette wheel selection method was implemented to choose parents for generating offsprings, where solutions are ranked in order of decreasing fitness, and the probability p^i of selecting the i^{th} ranked chromosome is: $2(N+1-i)/(N^2+N)$; where, *N* is the number of chromosomes in the pool. As desired, solutions at the top of the sorted list (i.e., with smaller weighted objective function value) have a higher probability of being selected, which in turn will ensure propagation of good structures onto the subsequent generations.

The selected chromosomes are subjected to a *mask* based Crossover operator to generate offsprings (table 2). A value of *1* in the *mask* implies swapping the corresponding itineraries of the chosen chromosomes (parents). For example, for the l^{th} demand, the corresponding itineraries are swapped between *C-3* and *C-24*. Note that there is no exchange of itineraries corresponding to a value of 0 in the mask (as for the j^{th} demand), and when the mating parents are using the same itinerary to meet a given demand (i.e., q^{th} demand). In an effort to find better solutions, neighborhoods of the resulting offsprings (*O/S-1* and *O/S-2*) are explored, which go on to replace the weaker chromosomes in the (starting) solution pool.

Demand	***j***	***k***	***L***	**..**	**..**	**..**	***q-2***	***q-1***	***Q***
C-3	X_1^j	X_1^k	X_2^l	..	..	..	X_5^{q-2}	X_5^{q-1}	X_3^q
C-24	X_1^j	X_1^k	X_3^l	..	..	..	X_5^{q-2}	X_7^{q-1}	X_3^q
Mask	***0***	***0***	***1***	**..**	**..**	**..**	***0***	***0***	***1***
O/S-1	X_1^j	X_1^k	X_3^l	..	..	..	X_5^{q-2}	X_5^{q-1}	X_3^q
O/S-2	X_1^j	X_1^k	X_2^l	..	..	..	X_5^{q-2}	X_7^{q-1}	X_3^q

Table 2: The Crossover operator

O/S	X_1^j	X_1^k	X_2^l	..	..	..	X_5^{q-2}	X_7^{q-1}	X_3^q

"index"

Table 3: Neighborhood Search

We implement a limited *first*-improvement neighborhood search scheme, in which each demand has its itinerary improved at most once. For example, a random "index" position is generated along the length of each offspring, followed by an examination of all solutions created by replacing the current itinerary with possible alternatives. For example, in table 3, the "index" is generated at the k^{th} demand position which is currently being met using the 1st itinerary. An evaluation is performed to see whether using any of the other available itineraries would result in a better solution. If a better solution is encountered as a result of the suggested scheme, it is accepted and becomes the new current solution. The exploration scheme moves to the next demand (l^{th}) either on encountering a first improvement or when none of the candidate solutions are better off than the current solution. This evaluation scheme continues till the index-counter returns immediately to the left of the starting position (i.e., j^{th} demand). The neighborhood of each offspring is explored in this manner, and the resulting solutions with better fitness value replace the less fit ones in the pool.

Two (separate) stopping conditions were experimented with. Under the *first* condition, the algorithm stops once a certain number of offsprings were generated. A number of experiments were performed to ascertain the appropriate number to consider, and they are discussed in subsection 5.2. The *second* stopping condition, implemented independently of the first, entailed algorithm termination if no improvement was registered for twenty-five consecutive offsprings. Note that this is equivalent to successive failures.

In figure 1 below, we provide a formal statement of the procedure devised for solving the tactical planning problem for railroad shipments of mixed freight.

INITIAL SOLUTIONS:

Step 1: Generate the first member via the solution to (P1).
Step 2: Generate the other members.
- Randomly pre-assign itineraries to demand classes,
- Solve (P1) after adding the induced constraints.

Step 3: Calculate the objective function value for (P).
- Assess the risk of each member of the pool using (6”) and (7”) via (P2).
- Evaluate each solution using a weighted average of cost and risk.

Step 4: Selection and Crossover.
- Use Roulette-wheel selection for identifying parents.
- Use MASK-based crossover for generating offsprings.

OFFSPRINGS:
Step 5: Local Search on the offspring:
- Use the limited *first*-improvement exploration.

STOPPING CRITERIA
Step 6: Repeat **Steps 3, 4** and **5** until:
- Pool-Size reaches 250.
- No improvement in 25 consecutive offsprings.

Figure 1: Summary of *Memetic Algorithm*

5. COMPUTATIONAL EXPERIMENTS

In this Section, we use the proposed methodology for solving eleven problem instances in order to develop managerial insights that could help managers for tactical planning. We ground model problem parameters in a real life problem setting from Midwest US, which is described in section 5.1. In section 5.2 we illustrate the use of the proposed methodology and in section 5.3 we report on our analyses conducted on the instances generated based on this problem setting.

5.1 Problem Setting

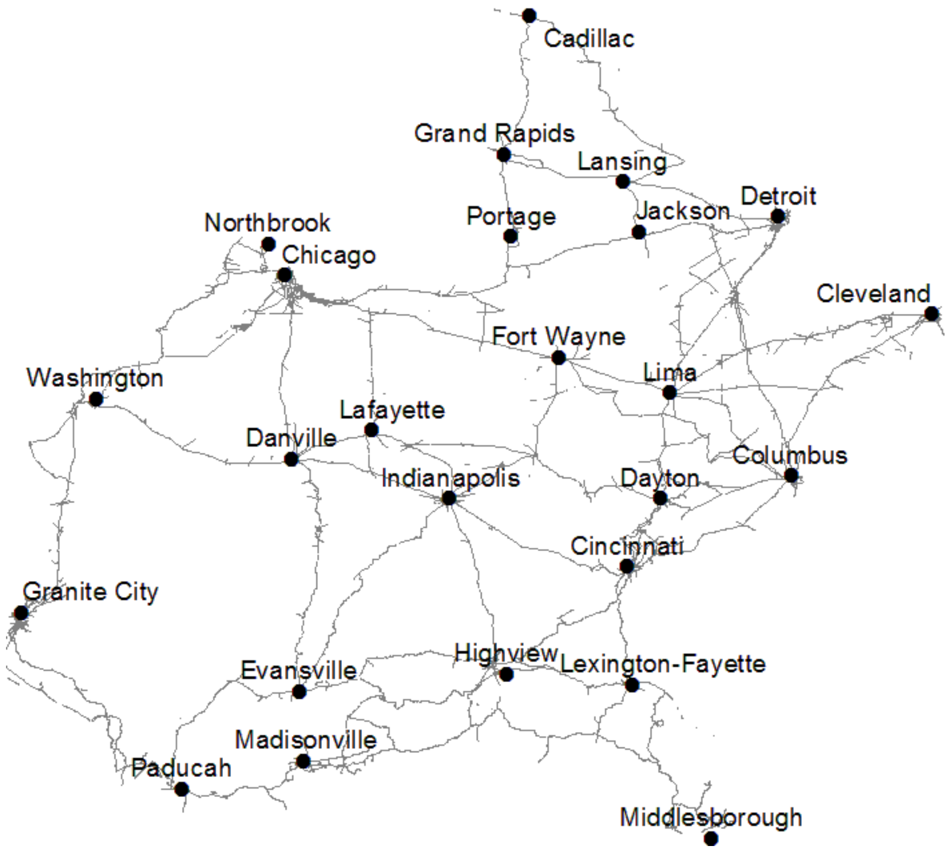

Figure 2: Railroad Network

Figure 2 represents the railroad infrastructure in Midwest US, which was used to generate realistic-size problem instances. There are twenty-five yards in the network, each represented by a node. Each node is both a demand and supply point for the others, and hence there are 600 origin-destination pairs. We use hypothetical demand data which were randomly generated utilizing the fuel oil consumption figures as compiled by the Department of Energy (http://tonto.eia.doe.gov). A total of 8,875 railcars (including 4,467 with hazardous cargo) have to be routed, wherein the order size range from 10 to 30 railcars (including 5 to 15 with hazardous cargo). 15 of the twenty-five yards are fully-equipped (classification and transfer operations are possible), while the remaining 10 can only perform transfer operations.

We have endeavored to replicate the service network of Norfolk Southern (NS), a Class I railroad operator, with extensive railroad network in eastern US. A total of 31 train services, created in ArcView GIS, connect the yards in the network. It is important that such trains are formed (and terminate) at fully-equipped yards since classification of railcars precedes the formation (and follows termination) of freight trains. It is important to note that each element in this problem setting, except hypothetical demand, is realistic and not random.

5.2 Solution of the Illustrative Problem

Two of the common techniques for solving multi-objective models, such as **(P)**, are pre-emptive optimization and weighted sums (Rardin, 1998). The former calls for a sequential solution process, while the latter associates weights to different objective values. We pose the tactical planning problem from the perspective of the railroad operator, who is interested in minimizing transport cost but is also under governmental pressure to consider transport related risk. Although we associate equal weights to both cost and risk objectives to solve the realistic problem instance, we also report in subsection 5.3 on a parametric analysis performed by associating different weights to the two objectives. Problem **(P)** was decomposed to generate (P1) and (P2). CPLEX Optimizer 8.1.0, with Simplex, Mixed Integer and Barrier Optimizer, was used to solve (P1) and determine the min cost solution (CPLEX, 2009). In addition, twenty-nine other solutions were determined by implementing the double-randomization technique described in section 4. The computation time ranged from around 0.22 seconds to 1094 seconds for a total of 2569 seconds. (P1) consisted of 1,337 binary and 31 integer variables, while the number of constraints for the thirty problems ranged from 2,144 for the min cost solution to 2,491 for the most constrained random solution. The risk assessment for each solution (chromosome) in the pool was conducted using (6”) and (7”) via (P2). The solution methodology was coded in Python, a dynamic object-oriented programming language. All numerical experiments were performed on an Apple, running Mac OS 10.5.6. and Python 2.6.1 (PYTHON, 2009).

	Number of Offspring			
Avg. CPU Time	**612 s**	**2441 s**	**4466 s**	**BEST**
RUN #	**100**	**250**	**500**	**SOLUTION**
1	*0.036%*	*0.018%*	*0.001%*	*571*
2	*0.016%*	*0.011%*	*0.002%*	*696*
3	*0.025%*	*0.012%*	*0.012%*	*596*
4	*0.044%*	*0.019%*	*0.017%*	*735*
5	*0.021%*	*0.014%*	*0.003%*	*663*

Table 4: Fine-tuning the *first* stopping condition

Before applying the *Memetic Algorithm* (MA) technique to solve the realistic problem instance, we tune the stopping condition. In an effort to ascertain the number of offsprings to consider, five independent simulations were performed wherein the algorithm was allowed to run until 1000 chromosomes (offsprings) were generated. Table 4 reports the average CPU time (in seconds) needed to generate 100, 250 and 500 offsprings and the respective gap from the best solution, and the number of offsprings generated before encountering the best solution.

Although in each of the five runs the best solution was encountered when more than 500 offsprings had been created, the size of gap motivated capping the runs at smaller number of offsprings. To that end, we decided to conduct all computational experiments by generating 250 offsprings, although 100 offsprings would also have resulted in a very acceptable gap of less than 0.5%.

We also considered the second stopping condition. To that end ten independent runs -at an average CPU time of 674.5 seconds -were performed, and where the algorithm terminated if there was no improvement in twenty-five consecutive offsprings. It was observed that the algorithm stopped after generating 50 to 140 offsprings, although the best solutions were reported later on. On closer examination it was noticed that solutions obtained under the first stopping condition (i.e., 250 offsprings) were superior to those under the second condition, and hence we implement just the first stopping condition to perform subsequent experiments.

	250 OFFSPRING			
RUNS	**CPU Time (sec)**	**Fitness**	**COST ($)**	**RISK (people)**
1	2468	7,889,228	*2,013,184*	*13,765,272*
2	2533	7,889,192	*2,021,481*	*13,756,904*
3	2547	7,886,857	*2,021,907*	*13,751,807*
4	2433	7,889,163	*2,021,489*	*13,756,837*
5	2500	7,887,520	*2,026,192*	*13,748,848*
6	2353	7,888,477	*2,017,948*	*13,759,007*
7	2539	7,889,339	*2,024,246*	*13,754,432*
8	2523	7,888,313	*2,021,256*	*13,755,370*
9	2279	7,888,927	*2,024,148*	*13,753,706*
10	2490	7,887,287	*2,022,051*	*13,752,526*
11	2445	7,888,837	*2,020,630*	*13,757,045*
12	2371	7,889,209	*2,025,309*	*13,753,109*
13	2477	7,888,788	*2,021,977*	*13,755,579*
14	2371	7,888,623	*2,018,519*	*13,758,727*
15	2317	7,888,705	*2,016,892*	*13,760,539*
16	2570	7,889,035	*2,022,030*	*13,756,041*
17	2295	7,888,265	*2,021,206*	*13,755,324*
18	2450	7,889,773	*2,019,412*	*13,754,134*
19	2590	7,888,811	*2,022,294*	*13,755,328*
20	2404	7,889,112	*2,020,618*	*13,757,607*
MEAN	2448	7,888,673	*2,021,139*	*13,755,907*
MIN	2279	7,886,857	*2,013,184*	*13,748,848*
MAX	2590	7,889,773	*2,026,192*	*13,765,272*
VARIANCE	8625	531,160	*8,843,030*	*12,100,897*

Table 5: Twenty Runs & Best Solutions

Details on the best solutions –represented as chromosome fitness –encountered in twenty independent runs, with the first stopping condition, are reported in table 5. A total of 5000 offsprings were generated, of which the best solution in terms of *fitness* (highlighted) was encountered in the third random run. The table also lists the mean, min, max and variance for each of the four attributes. It is interesting, perhaps not unexpected, that although fitness values seem to be clustered (i.e., low variance), the actual variability of the embedded objectives is significant. It is important to note that the fitness values, in table 5, stem from associating equal weight (i.e., 0.5) to both the cost and risk objective. Insights resulting from associating different weights to the two objectives are discussed in the next subsection. We designate the best encountered solution the *Base-Case*, and decode it to analyze the cost and risk impact on the given railroad network.

Table 6 provides relevant information about the different train services being used to meet demand, and also the impact at the yards. For example, the first row represents the train service that originates in Chicago and terminates in Detroit, and has two intermediate stops (not listed, but they are Portage and Jackson). Three trains of this type would be required, incurring a fixed cost of $2751, and exposing 35,322 people. Corresponding parameters for other train services can be interpreted similarly. A total of 97 trains, costing just under $170K and exposing around 1.96 million people, would be needed to meet the demand in the network. The variable cost to route railcars to the respective destination yards amounts to $1,852,148. A total of 11,793,099 people would be exposed due to yard operations, with the yards at Chicago, Cincinnati, Cleveland, Columbus, Detroit, Indianapolis, and Lexington-Fayette accounting for 75% of the exposure. The concentration of risk around these yards is also underlined in the number of trains emanating and terminating at these yards. This is because yard operations leading to the departure of twenty-five, and termination of twenty, trains have to be performed at these yards. Finally, the high expected risk at these yards is a good surrogate measure to justify installation of commensurate emergency response system. It is important to note that, for this problem instance, around 85% of the network risk results from yard operations i.e., 11,793,099/13,751,807. This finding is consistent with the literature on accident probabilities, which states that most of the accidents happen during loading /unloading and classification/transfer operations at yards, and not when the train is moving.

Origin	Destination	No. of Stops	No. of Trains	COST ($)	RISK (people)
Chicago	Detroit	2	3	2751	35322
Chicago	Cleveland	3	2	2686	31948
Chicago	Columbus	3	2	2240	23946
Chicago	Indianapolis	2	3	2691	23457
Chicago	Lexington-Fayette	3	3	4011	62293
Chicago	Middlesborough	5	4	11572	223317
Detroit	Indianapolis	3	5	6100	55277
Detroit	Middlesborough	4	3	4881	56981
Detroit	Cleveland	3	3	5520	20837
Grand Rapids	Columbus	5	9	19260	321364
Indianapolis	North Brook	3	2	2700	38742
Indianapolis	Middlesborough	3	4	8360	51372
Indianapolis	Cadillac	2	3	4011	10457
Indianapolis	Cleveland	3	2	2694	24662
Indianapolis	Columbus	2	2	1726	16809
Indianapolis	Chicago	3	2	2546	24095
Columbus	Chicago	3	3	4200	23066
Columbus	Granite City	4	3	6531	45504
Columbus	Cadillac	3	4	5640	48429
Columbus	Madisonville	3	2	3920	22687
Cleveland	Chicago	3	5	6715	51773
Cleveland	Paducah	5	3	6591	71322
Cincinnati	Detroit	4	2	2960	31050
Lexington-Fayette	Chicago	3	2	3206	31202
Lexington-Fayette	Chicago (2nd)	5	7	19250	400827
Lexington-Fayette	Grand Rapids	6	1	2367	46185
Middlesborough	Fort Wayne	3	1	1593	19141
Madisonville	Detroit	4	5	9650	46869
Paducah	Columbus	3	3	4959	37443
Middlesborough	Cleveland	3	1	1537	12111
Middlesborough	Detroit	5	3	6891	50220
COST			**RISK**		
- Fixed Train:		$169,759	- Tracks:		1,958,708
- Variable (routing and yard):		$1,852,148	- Yards:		11,793,099
Total:		**$2,021,907**	**Total:**		**13,751,807**

Table 6: *Base-Case* Solution

5.3 Managerial Insights

To explore trade-offs between cost and risk, 100 additional runs, corresponding to weight combinations between (1, 0) and (0, 1) by increments of 10%, but excluding the (0.5, 0.5) *Base-Case*, were performed. Results obtained for the 100 runs are summarized in table 7. The CPU time (in seconds) is the average for ten runs, for each weight combination, and the solution with the best fitness value is displayed.

LEGENDS	Avg. time (s)	COST ($)	RISK (people)	No. of Trains
Min Cost	3449	1,941,280	14,784,901	92
A = [cost=0.9, risk=0.1]	2444	1,956,385	14,061,713	92
B = [cost=0.8, risk=0.2]	2521	1,978,835	13,862,452	93
C = [cost=0.7, risk=0.3]	2547	2,010,784	13,770,222	97
D = [cost=0.6, risk=0.4]	2440	2,014,376	13,761,336	96
Base Case	2435	2,021,907	13,751,807	97
E = [cost=0.4, risk=0.6]	2482	2,032,784	13,741,740	97
F = [cost=0.3, risk=0.7]	2448	2,042,393	13,739,152	99
G = [cost=0.2, risk=0.8]	2433	2,048,606	13,734,451	100
H = [cost=0.1, risk=0.9]	2400	2,052,979	13,734,152	100
Min Risk	2399	2,069,129	13,733,922	102

Table 7: Risk-Cost Numbers

In this table, each row represents a non-dominated solution, with the *min cost* and the *min risk* solutions constituting the two extremes. While the *min cost* solution resulted in maximum risk, the *min risk* solution was the most expensive. The *min cost* solution is 4% less expensive, but 7.5% more risky than the *Base-Case* solution. Although a reduction in the number of trains (92 against 97) is partially responsible for the decreased cost, the exposure around the rail tracks has increased by 5%. The impact of better train utilization was reflected primarily in higher hazmat (and total) traffic through the yards at Chicago, Columbus and Cincinnati, thereby increasing the population exposure at yards by 989,161 people. On the other hand the *min risk* solution is 2.3% more expensive than the *Base Case,* in part due to the larger number of trains needed in the network (102 against 97). The decrease in population exposure was reflected in the reduced traffic (and hence risk) at the Indianapolis yard.

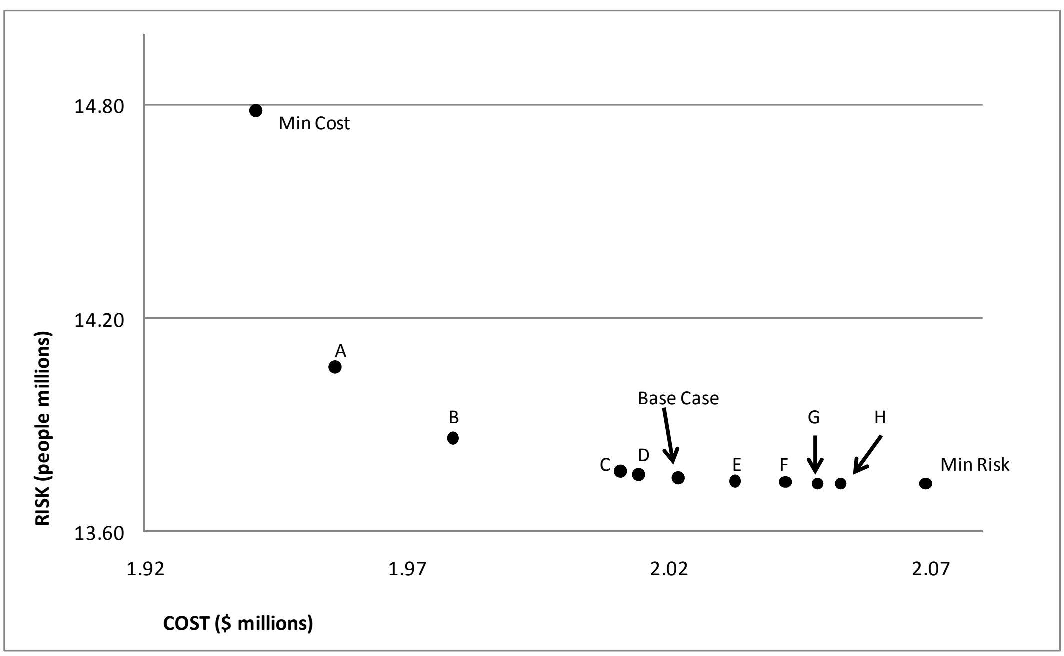

Figure 3: Weight Based Solutions

From Table 7 (and fig. 3) one sees that the *min cost* solution entails cost of $1.94 million and exposes 14.8 million people, whereas the *min risk* solution will cost around $2.1 million and expose 13.7 million people. By spending an extra $128K, it is possible to reduce population exposure risk by 1.14 million. This may be a worthwhile trade-off for the regulators to pursue. Perhaps a more important observation is the significant increase in population exposure risk when the weight associated to the risk coefficient is decreased from 10% to 0% (i.e., from *A* to *Min Cost*). This weight allocation results in a saving of around $15K but increases exposure by 720K, which implies that every dollar saved exposes 48 additional individuals to hazmat risk.

5.4 Quasi Pareto-Solutions

In an effort to provide the decision-makers with a set of non-dominated solutions, all (quasi) Pareto solutions were captured. Of the 7500 offsprings, generated as a result of the 120 independent runs, fifty-six quasi Pareto solutions were identified among the computed solutions. These (quasi) Pareto solutions, including the ones discussed in the previous subsection, are depicted in figure 4.

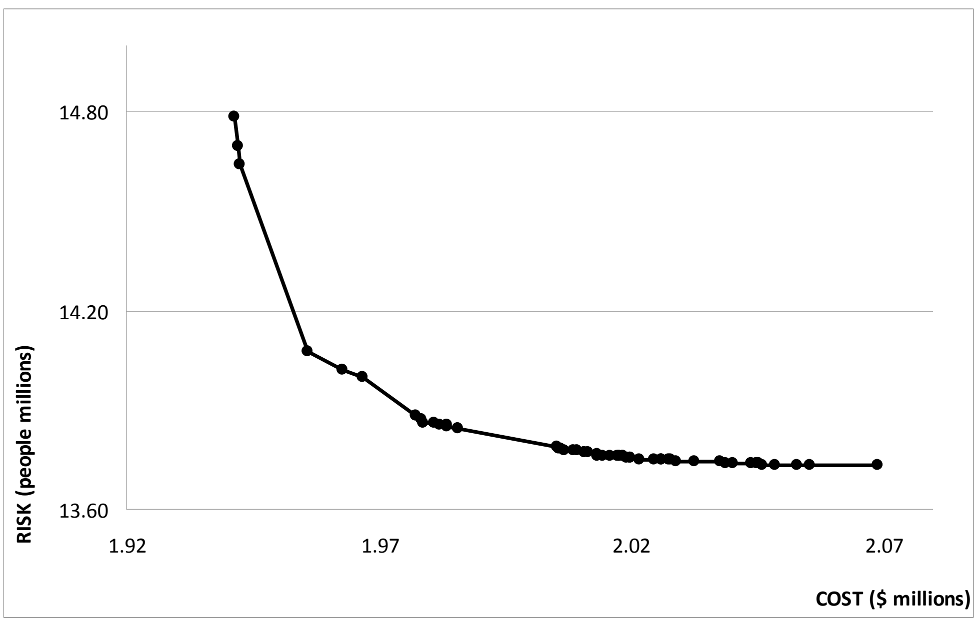

Figure 4: Partial Pareto-Frontier

It is important to note that this is just a portion of the possible (quasi) Pareto-frontier, which should ideally list *all possible* non-dominated solutions. Since quantification of risk is one of the most challenging and contentious issues in hazmat transport, such a (partial) frontier could be used by the primary stakeholders to conduct judicious evaluation of the monetary and societal implications of hazmat transportation.

6. CONCLUSION

In this paper, we incorporate the rail risk assessment methodology, developed in Verma and Verter (2007), to solve tactical planning problems of railroad companies. The resulting distinctive feature of our model is its ability to capture the economies of risk on railroads, whenever more than one railcar with potentially hazardous cargo travels on the same train.

The absence of a closed-form expression for the risk objective necessitated the development of a meta-heuristic based solution methodology. The proposed Memetic Algorithm, which combines the attributes of genetic and local searches, determines the routing of individual railcars, the number of different train types required in the system, and the different yard operations. The railroad infrastructure in Midwest US was used as a basis for generating realistic-size problem instances, which were solved to gain additional insights into the problem structure. A number of non-dominated solutions were identified to develop a (quasi) Pareto-frontier, which could be used by the two primary stakeholders, i.e., regulatory agencies and transport companies, to make judicious decisions in an effort to (mitigate) avoid what happened in Lafayette (US) in May, 2008.

This work has a three-fold contribution. *First*, this is the first tactical planning model for railroad transportation of hazmat where transport risk assessment incorporates the distinctive features of railroad operations. *Second*, this is the only work that provides an insight into the yard and line activities, given the incorporation of the population exposure risk measure in the decision making framework. *Third*, this is the only application of a Memetic Algorithm based solution methodology that generates a number of non-dominated solutions, for the risk-cost trade-off frontier, to be used for planning railroad tactical problems.

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