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Planning and managing intermodal transportation of hazardous materials with capacity selection and congestion

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ABSTRACT

The current literature in the rail–truck intermodal transportation of hazardous materials (hazmat) domain ignores congestion at intermodal yards. We attempt to close that gap by proposing a bi-objective optimization framework for managing hazmat freight that not only considers congestion at intermodal yards, but also determines the appropriate equipment capacity. The proposed framework, i.e., a non-linear MIP and a multi-objective genetic algorithm based solution methodology, is applied to a realistic size problem instance from existing literature. Our analysis indicates that terminal congestion risk is a significant portion of the network risk; and, that policies and tools involving number of cranes, shorter maximum waiting times, and tighter delivery times could have a positive bearing on risk.

1. Introduction

Intermodal transportation, defined as the transportation of goods by a sequence of at least two different modes, continues to be one of the dominant segments of the transportation industry. Rail–truck intermodal transportation, which exploits the positive attributes of both trains and trucks, has experienced phenomenal growth since 1980 (AAR, 2010). According to the most recent study commissioned by the Department of Transportation, rail–truck intermodal traffic, measured in ton-miles, increased by 254% between 1993 and 2007 (US DOT, 2010). Note that the attractiveness of rail–truck intermodal transportation (RTIM), in part, stems from two sources: *first*, the significant reduction in both delivery and lead-time uncertainty because of the schedule-based operation of intermodal trains (Nozick and Morlok, 1997); and, *second* a more efficient and cost-effective overall movement ensured by combining the best attributes of the two modes (AAR, 2010).

Although intermodal transportation, in general, has received increasing attention from researchers over the past two decades, most of the discussion is focused on regular freight (SteadieSeifi et al., 2014; Macharis and Bontekoning, 2004). This is problematic since RTIM has also been used to move hazardous materials (hazmat), and the dependence of the industrialized society on hazmat has translated into a steady increase in volume over the past four decades. For example, the Bureau of Transportation Statistics estimated that the hazmat volume across the US intermodal transportation system increased from 1.5 million tons in 1997 to 111 million tons in 2007 (US DOT, 2004, 2010). It is important that such estimates are still on the conservative end, given that around one-quarter of chemicals are moved on railroads (AAR, 2009), and the projection of the US Chemical Manufacturers Association that the total volume of hazmat shipped by 2020 will be around 5.1 billion tons.

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In an effort to both motivate the need for this study and also to position it within the existing literature, we note that RTIM comprises three processes: (i) inbound drayage, (ii) rail haul and, (iii) outbound drayage. A significant portion of the transport distance is covered by intermodal trains, which operate on a fixed-schedule and hence are quite punctual. On the other hand drayage is carried out by truck, with inbound referring to the transport activity between a shipper and origin intermodal terminal, and outbound to that between a receiver and destination terminal. To the best of our knowledge, there are only seven refereed publications on intermodal transportation of hazmat. In one of the earliest studies, Mazzarotta (2002) presented a quantitative risk analysis approach for hazmat transportation, wherein risk mainly depended on the hazardous characteristics of the product. The author examined the data for Italy, and made the case for moving some transport activity from road to rail–truck intermodal. In a subsequent study, Bubbico et al. (2006) made use of three classes of hazmat to show that risk mitigation was possible by not just changing the route but also by using a different transportation mode. A total of 55 cases were analyzed, and the resulting analysis suggested that it was worthwhile to move some hazmat from road to rail or to intermodal to reduce risk. Since the objective of these studies was to compare risk stemming from road to that from rail–truck intermodal, not much attention was paid to modeling the characteristics of an RTIM system. To close that gap, Verma and Verter (2008) built an illustrative case study based in Canada to understand the trade-offs associated with rail–truck intermodal transportation of hazmat. The resulting insights were used to develop an analytical framework for planning rail–truck intermodal transportation across a network when shipper/receivers have access to a single terminal (Verma and Verter, 2010), and to multiple terminals (Verma et al., 2012). Given the exploratory nature of the studies, congestion at intermodal terminals was ignored by assuming enough equipment such that a just-in-time system could be implemented. Moreover, since delivery lead-times drove the selection of intermodal paths – feasible solution was possible only if at least one viable path existed. In a subsequent work, Verma (2012) relaxed the assumption about at least one viable path by adding a penalty function for late deliveries. Finally, Xie et al. (2012) studied the facility location and routing problem for multimodal transportation of hazmat by considering cost and risk stemming from both the transport and terminal location.

It is clear from the above studies that hazmat risk has been considered at the strategic and the tactical levels when planning intermodal hazmat freight, although the focus was only on decisions about transport and intermodal terminal location, while the issue of congestion at the terminals has been ignored. It is important that congestion at a terminal could likely affect the flow of traffic throughout a given network (SEROps, 2008), and thus postulate that accumulation of hazmat containers would increase the potential of incidents for the surrounding areas. Hence, there is a need to develop an analytical framework that takes into consideration the issue of congestion along the intermodal chain, especially at the terminals. Doing so would not only facilitate a better understanding of the resulting trade-offs, but also aid the appropriate equipment capacity decisions. It is important to note that although the impact of capacity on congestion has been well studied within the facility location literature, we are not aware of any effort involving hazmat freight. Hence, for capturing congestion (consistent with the existing literature, e.g., Elhedhli and Hu, 2010; Ishfaq and Sox, 2012; Marianov and Serra, 2003), we model arrivals of both regular and hazmat freight at the intermodal terminals as a Markovian queue. In this paper, we study the impact of terminal congestion and equipment capacity selection on the routing of regular and hazmat freight through a rail–truck intermodal network. Hence, this work is an extension of Verma et al. (2012) since both equipment selection and congestion at intermodal terminals are being considered. We pose the problem from the perspective of the intermodal railroad company, which offers a door-to-door service to the customers. In order to address the interest of both intermodal companies and regulatory agencies, we propose a bi-objective nonlinear programming model that considers both cost and risk, and solution methodology that combines the attributes of non-dominated sorting genetic algorithm and CPLEX.

In an effort to capture the hazmat volume and the resulting consequence, we resort to a more aggregate measure in this paper: *population exposure*. We represent transport risk as the total number of people exposed to the possibility of an undesirable consequence due to the shipment. For example, according to the North American Emergency Response Guidebook (2008), 800 m 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. This fixed bandwidth approach was first suggested by Batta and Chiu (1988), ReVelle et al. (1991), and has been used by many authors since then.

The rest of the paper is organized as follows. In Section 2 we define the managerial problem of interest, highlight the complexity and then outline the assumptions. Section 3 presents the nonlinear bi-objective optimization framework, the technique to estimate cost and risk parameters, and finally an outline of the genetic-algorithm based solution methodology. Section 4 makes use of the intermodal infrastructure of a Class I railroad operator to generate a number of problem instances of realistic size, which are solved and analyzed to gain managerial insights. Conclusion, contributions and directions of future research are outlined in Section 5.

2. Problem statement

In this section, we provide a formal statement of the problem, emphasize its complexity, and then state the modeling assumptions.

Our problem is to determine the best shipment plan for both hazardous and non-hazardous freight in an RTIM network, wherein a set of pre-defined lead times must be satisfied in choosing the truck routes and the intermodal train services to be used. The objective is to minimize the total cost as well as the total public risk associated with intermodal hazmat shipments. This task is complicated because hazmat risk at terminals needs to be determined by modeling congestion using Markovian queues, which in turn will drive the decision about equipment capacity (acquisition or operations) decisions, and only then

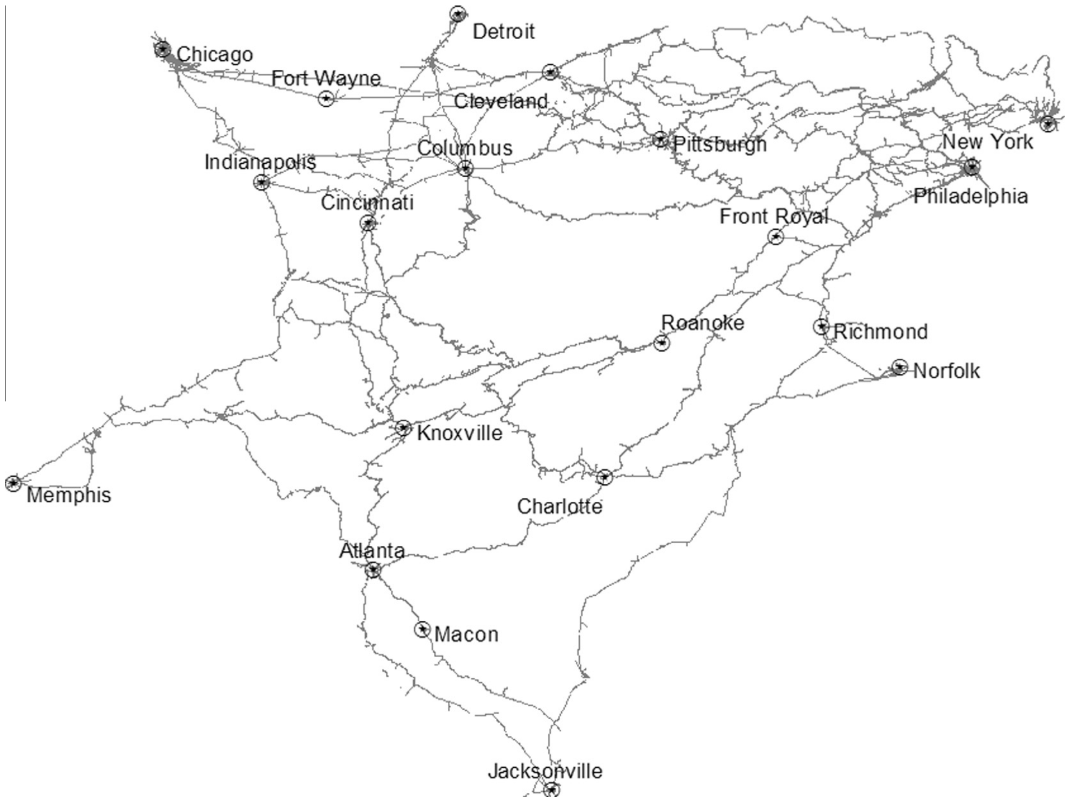

Fig. 1. Intermodal network of Verma et al. (2012).

intermodal freight routing decisions can be made. Furthermore, it is also necessary to streamline the inbound drayage, intermodal rail haul and outbound drayage activities while making the trade-off between total cost and total public risk.

In an effort to succinctly explain the complexity of the problem, we reproduce the intermodal service chain network introduced in Verma et al. (2012), which is represented via a geographical information system (GIS) model using ArcView (ESRI, 2008). Fig. 1 depicts the 20 intermodal terminals, which are the access points for 37 shippers/receivers located in the surrounding regions. A total of 62 types of intermodal train services differentiated by route and intermediate stops are connecting these terminals, i.e., 31 trains of *regular* type, and another 31 of *priority* type that is 25% faster. Finally, we assume that the decision maker selects a number of equipment with identical characteristics for possible acquisition at each terminal. Note that any selected equipment, in turn, is the server for a non-preemptive priority queue, and whose clients are processed according to assigned priorities (Gross et al., 2008). More specifically, hazmat containers have priority over regular containers, i.e., hazmat containers move to the head of the queue although the ongoing processing of regular freight is not interrupted. This approach not only enables one to utilize hazmat quantity as a surrogate for risk, but also conforms to the stipulation surrounding storage and handling of dangerous goods, viz. minimize the hazmat volume at a storage location by substituting it with less risky commodities (SHDG, 2005).

We now turn to our modeling assumptions: *first,* "period" in our study refers to a certain time unit during which the demand remains relatively stable. *Second*, we assume that both hazmat and regular containers arrive, independently, at the terminals according to a Poisson process; and, that the service time of the equipment is exponentially distributed. This assumption is consistent with the existing literature for modeling congestion (Rajagopalan and Yu, 2001). *Third*, a rail–truck intermodal shipment is feasible, only if the total time needed to complete the drayage and rail-haul activities is less than the pre-specified delivery time. In order to ease the lead-time calculations, we assume that intermodal trains of the same service class (i.e., speed) that operate on the same route arrive at the destination terminal around the same time. Therefore, if the maximum train length is exceeded, then the containers that belong to a shipment can be split between such trains without affecting their delivery time.

3. Optimization framework

In this section, we provide a nonlinear mathematical formulation for the managerial problem and then discuss the estimation of the basic parameters of the model in Section 3.2. In Section 3.3, we present a genetic algorithm based solution methodology to solve the problem.

3.1. Model formulation

Our notation and the model (**P**) is provided below.

Sets	
I	set of shippers, indexed by i
J	set of origin terminals, indexed by j
K	set of destination terminals, indexed by k
L	set of receivers, indexed by l
Z_{il}	set of shipper–receiver pairs with demand for freight (i.e., traffic class), indexed by z
P_{ij}	set of inbound drayage paths between shipper i and origin terminal j, indexed by p
Q_{kl}	set of outbound drayage paths between destination terminal k and receiver l, indexed by q
V_{jk}	set of intermodal trains between origin terminal j and destination terminal k, indexed by v
S_{jk}^{v}	set of service legs for train v between terminals j and k, indexed by s
M_j	set of equipment under consideration at origin terminal j, indexed by m
M_k	set of equipment under consideration at origin terminal j, indexed by m'
Variables	
X_z^p	rate of hazmat containers of traffic-class z using path p for inbound drayage
$\overline{X}_z^p$	rate of regular containers of traffic-class z using path p for inbound drayage
X_z^v	rate of hazmat containers from traffic-class z on train service of type v
$\overline{X}_z^v$	rate of regular containers from traffic-class z on train service of type v
X_z^q	rate of hazmat containers of traffic-class z using path q for outbound drayage
$\overline{X}_z^q$	rate of regular containers of traffic-class z using path q for outbound drayage
N^v	number of intermodal trains of type v
λ_j^m	expected arrival rate of hazmat containers at equipment m in origin terminal j
$\bar{\lambda}_j^m$	expected arrival rate of regular containers at equipment m in origin terminal j
$\lambda_k^{m'}$	expected arrival rate of hazmat containers at equipment m in destination terminal k
$\bar{\lambda}_k^{m'}$	expected arrival rate of regular containers at equipment m in destination terminal k
H_j^m	1 if equipment m is acquired at origin terminal j; 0 otherwise
$H_k^{m'}$	1 if equipment m' is acquired at destination terminal k; 0 otherwise
Indicator variables	
Y_z^p	1 if $X_z^p > 0$; 0 otherwise
$\overline{Y}_z^p$	1 if $\overline{X}_z^p > 0$; 0 otherwise
Y_z^v	1 if $X_z^v > 0$; 0 otherwise
$\overline{Y}_z^v$	1 if $\overline{X}_z^v > 0$; 0 otherwise
Y_z^q	1 if $X_z^q > 0$; 0 otherwise
$\overline{Y}_z^q$	1 if $\overline{X}_z^q > 0$; 0 otherwise
Parameters	
C^p	cost of moving one hazmat container on path p for inbound drayage
$\overline{C}^p$	cost of moving one regular container on path p for inbound drayage
C^v	cost of moving one hazmat container on intermodal train service of type v
$\overline{C}^v$	cost of moving one regular container on intermodal train service of type v
C^q	cost of moving one hazmat container on path q for outbound drayage
$\overline{C}^q$	cost of moving one regular container on path q for outbound drayage
B_j	cost to purchase equipment at origin terminal j
B_k	cost to purchase equipment at destination terminal k
FC^v	fixed cost of operating intermodal train service of type v
E^p	exposure from moving one hazmat container on path p for inbound drayage
E^v	exposure from moving one hazmat container on intermodal train service of type v
E^q	exposure from moving one hazmat container on path q for outbound drayage
E_j	exposure resulting from one hazmat container in the queue at origin terminal j
E_k	exposure resulting from one hazmat container in the queue at destination terminal k
t^p	time to complete inbound drayage using path p
t^v	time to complete rail haul using intermodal train service of type v
t^q	time to complete outbound drayage using path q
DT_z	customer specified delivery time for traffic class z
U^v	maximum number of containers that each intermodal train service of type v can load

μ_j	service rate of equipment at origin terminal j
μ_k	service rate of equipment at destination terminal k
D_z	rate of hazmat containers demanded in traffic class z
$\overline{D}_z$	rate of regular containers demanded in traffic class z

(P) Minimize

Total Cost:

$$\sum_{z\in Z_{il}}\sum_{p\in P_{ij}}\left[C^pX_z^p+\overline{C}^p\overline{X}_z^p\right]+\sum_{z\in Z_{il}}\sum_{v\in V_{jk}}\left[C^vX_z^v+\overline{C}^v\overline{X}_z^v\right]+\sum_{z\in Z_{il}}\sum_{q\in Q_{kl}}\left[C^qX_z^q+\overline{C}^q\overline{X}_z^q\right]+\sum_{v\in V_{jk}}FC^vN^v+\sum_{j\in J}\sum_{m\in M_j}B_jH_j^m$$
$$+\sum_{k\in K}\sum_{m'\in M_k}B_kH_k^{m'} \tag{1}$$

Total Public Risk:

$$\sum_{z\in Z_{il}}\sum_{p\in P_{ij}}E^pX_z^p+\sum_{z\in Z_{il}}\sum_{v\in V_{jk}}E^vX_z^v+\sum_{z\in Z_{il}}\sum_{q\in Q_{kl}}E^qX_z^q+\sum_{j\in J}\sum_{m\in M_j}E_j\lambda_j^m\frac{\lambda_j^m+\bar{\lambda}_j^m}{\mu_j\left(\mu_j-\lambda_j^m\right)}+\sum_{k\in K}\sum_{m'\in M_k}E_k\lambda_k^{m'}\frac{\lambda_k^{m'}+\bar{\lambda}_k^{m'}}{\mu_k\left(\mu_k-\lambda_k^{m'}\right)}$$

Subject to:

$$\begin{aligned}
&\sum_{p\in P_{ij}}X_z^p=\sum_{v\in V_{jk}}X_z^v\quad \forall j\in J,\forall z\in Z_{il} && \text{(a)}\\
&\sum_{p\in P_{ij}}\overline{X}_z^p=\sum_{v\in V_{jk}}\overline{X}_z^v\quad \forall j\in J,\forall z\in Z_{il} && \text{(b)}\\
&\sum_{v\in V_{jk}}X_z^v=\sum_{q\in Q_{kl}}X_z^q\quad \forall k\in K,\forall z\in Z_{il} && \text{(c)}\\
&\sum_{p\in P_{ij}}\overline{X}_z^p=\sum_{q\in Q_{kl}}\overline{X}_z^q\quad \forall k\in K,\forall z\in Z_{il} && \text{(d)}
\end{aligned} \tag{2}$$

$$\begin{aligned}
&\sum_{q\in Q_{kl}}X_z^q=D_z\quad \forall z\in Z_{il} && \text{(a)}\\
&\sum_{q\in Q_{kl}}\overline{X}_z^q=\overline{D}_z\quad \forall z\in Z_{il} && \text{(b)}
\end{aligned} \tag{3}$$

$$\sum_{z\in Z_{il}}\left[X_z^v+\overline{X}_z^v\right]\leqslant U^vN^v\quad \forall v\in V_{jk}\cap S_{jk}^v \tag{4}$$

$$\begin{aligned}
&\sum_{z\in Z_{il}}\sum_{p\in P_{ij}}X_z^p=\sum_{m\in M_j}\lambda_j^m\quad \forall j\in J && \text{(a)}\\
&\sum_{z\in Z_{il}}\sum_{p\in P_{ij}}\overline{X}_z^p=\sum_{m\in M_j}\bar{\lambda}_j^m\quad \forall j\in J && \text{(b)}\\
&\sum_{z\in Z_{il}}\sum_{q\in Q_{kl}}X_z^q=\sum_{m'\in M_k}\lambda_k^{m'}\quad \forall k\in K && \text{(c)}\\
&\sum_{z\in Z_{il}}\sum_{q\in Q_{kl}}\overline{X}_z^q=\sum_{m'\in M_k}\bar{\lambda}_k^{m'}\quad \forall k\in K && \text{(d)}
\end{aligned} \tag{5}$$

$$\begin{aligned}
&t^pY_z^p+t^vY_z^v+t^qY_z^q+\frac{\lambda_j^m+\bar{\lambda}_j^m}{\mu_j\left(\mu_j-\lambda_j^m\right)}+\frac{\lambda_k^{m'}+\bar{\lambda}_k^{m'}}{\mu_k\left(\mu_k-\lambda_k^{m'}\right)}+\frac{1}{\mu_j}+\frac{1}{\mu_k}\leqslant DT_z\\
&\forall p\in P_{ij},\forall v\in V_{jk},\forall q\in Q_{kl},\forall z\in Z_{il},\forall j\in J,\forall m\in M_j,\forall k\in K,\forall m'\in M_k && \text{(a)}\\
&t^p\overline{Y}_z^p+t^v\overline{Y}_z^v+t^q\overline{Y}_z^q+\frac{\lambda_j^m+\bar{\lambda}_j^m}{\left(\mu_j-\lambda_j^m-\bar{\lambda}_j^m\right)\left(\mu_j-\lambda_j^m\right)}+\frac{\lambda_k^{m'}+\bar{\lambda}_k^{m'}}{\left(\mu_k-\lambda_k^{m'}-\bar{\lambda}_k^{m'}\right)\left(\mu_k-\lambda_k^{m'}\right)}+\frac{1}{\mu_j}+\frac{1}{\mu_k}\leqslant DT_z\\
&\forall p\in P_{ij},\forall v\in V_{jk},\forall q\in Q_{kl},\forall z\in Z_{il},\forall j\in J,\forall m\in M_j,\forall k\in K,\forall m'\in M_k && \text{(b)}
\end{aligned} \tag{6}$$

$$\begin{aligned}
&\lambda_j^m+\bar{\lambda}_j^m\leqslant OH_j^m\quad \forall j\in J,\forall m\in M_j && \text{(a)}\\
&\lambda_k^{m'}+\bar{\lambda}_k^{m'}\leqslant OH_k^{m'}\quad \forall k\in K,\forall m'\in M_k && \text{(b)}
\end{aligned} \tag{7}$$

$$\begin{aligned}
&\lambda_j^m + \bar{\lambda}_j^m \leqslant \mu_j \quad \forall j \in J, \forall m \in M_j && \text{(a)} \\
&\lambda_k^{m'} + \bar{\lambda}_k^{m'} \leqslant \mu_k \quad \forall k \in K, \forall m' \in M_k && \text{(b)}
\end{aligned} \tag{8}$$

$$\begin{aligned}
&OY_z^p \geqslant X_z^p \quad \forall p \in P_{ij}, \forall z \in Z_{il} && \text{(a)} \\
&O\bar{Y}_z^p \geqslant \bar{X}_z^p \quad \forall p \in P_{ij}, \forall z \in Z_{il} && \text{(b)} \\
&OY_z^v \geqslant X_z^v \quad \forall v \in V_{jk}, \forall z \in Z_{il} && \text{(c)} \\
&O\bar{Y}_z^v \geqslant \bar{X}_z^v \quad \forall v \in V_{jk}, \forall z \in Z_{il} && \text{(d)} \\
&OY_z^q \geqslant X_z^q \quad \forall q \in Q_{kl}, \forall z \in Z_{il} && \text{(e)} \\
&O\bar{Y}_z^q \geqslant \bar{X}_z^q \quad \forall q \in Q_{kl}, \forall z \in Z_{il} && \text{(f)}
\end{aligned} \tag{9}$$

Sign restriction constraints on flow variables: $X \geqslant 0$ *integer*; $\lambda \geqslant 0$ *integer*; $N \geqslant 0$ *integer*; $H \in \{0,1\}$; $Y \in \{0,1\}$; and, O is a larger positive integer.

(P) is a bi-criteria nonlinear optimization model, with cost and risk objectives as represented in (1). The cost objective contains inbound drayage cost, rail haul cost, outbound drayage cost, fixed cost to operate different types of intermodal train services, and the equipment acquisition cost at the terminals. The risk objective contains population exposure due to drayage, various intermodal trains, and from terminal congestion. We simulate the congestion risk by finding the product of the terminal risk and the average number of hazmat containers waiting to be served (L_j^m). Based on the Little's law, we have: $L_j^m = \lambda_j^m w_j^m$, where $w_j^m = \frac{\lambda_j^m + \bar{\lambda}_j^m}{\mu_j(\mu_j - \lambda_j^m)}$ is the average time a hazmat container spends in the priority queue system. It is important that the focus of this study is on congestion risk at intermodal terminals, and hence the impact of uncertain travel time and congestion on transport links have been ignored. Constraint set (2) represents the transhipment function being performed by different terminals, by connecting drayage to the different types of intermodal train service in the network. It should be noted that transhipment constraints for hazmat and regular freight have to be distinguished in order to track them separately. Constraint set (3) ensures that each receiver's hazmat and regular freight demands are satisfied. Constraint set (4) states that the number of intermodal trains of a specific type will be determined by the total number of containers to be moved between two consecutive terminals (i.e., one a train service leg). Constraint set (5) ensures that the arrival rate for equipment at a terminal is equal to the number of hazmat and regular containers arriving at that terminal, or leaving that terminal for receiver locations. Constraint set (6) ensures that shipments reach the receiver before the specified delivery times. Note that the total time is equal to the time spent to complete drayage; rail haul; and, average waiting and processing time at the terminals, which collectively render these constraint sets non-linear. The average waiting time that a regular container spends in the queue is $\frac{\rho_j^m}{(1-\rho_j^m)(\mu_j - \lambda_j^m)}$, where $\rho_j^m = \frac{\lambda_j^m + \bar{\lambda}_j^m}{\mu_j}$ is the utilization rate of the queuing system. Constraint set (7) ensures that a request is assigned to equipment only if that is available (or purchased). Constraint set (8) enforces the steady-state conditions of the queuing systems (i.e., arrival rate at equipment cannot exceed its service rate). Constraint set (9) captures activation of indicator variables associated with different links, and this information is used in (6) to evaluate the feasibility of including that link in forming an intermodal chain. Note that O refers to a large positive integer, which is at least as big as the largest demand in the given network. Finally, there are sign restriction constraints on the variables, which have been represented as a group for compactness.

3.2. Estimation of model parameters

3.2.1. Cost

We first focus on the cost parameters, which have been borrowed from the existing peer reviewed works. In the United States, trucks can travel at a maximum speed of 50 miles/h, but due to lights and traffic an average speed of 40 miles/h is assumed. Normally drayage is charged in terms of the amount of time the crew (driver-truck) is engaged, and an estimate of \$250/h including the estimated hourly fuel cost is used (Verma et al., 2012). For example, if it takes four hours to complete inbound drayage (including travel and waiting time), the associated cost is \$1000. Furthermore, it is estimated that approximately one hour is needed to load, unload, or transfer an intermodal container. Barton et al. (1999) estimated \$140 to be the cost of a lift at the intermodal yard, but we assume \$150 to reflect the current conditions.

There are two types of intermodal train services between each terminal pair (viz. *regular* and *priority*), whose travel time includes two hours for loading and unloading at every terminal they visit. Average intermodal train speed was calculated using the Railroad Performance Measure website (RPM, 2008), and was estimated to be 27.7 miles/h for *regular*, and 36.8 miles/h for *priority* service. Although Morlok and Spasovic (1995) estimated \$0.70/mile as the intermodal rail-haul cost, a rate of \$0.875/mile has been estimated for *regular* and \$1.164/mile for *priority* service. The hourly fixed cost of running a *regular* intermodal train is \$500 per hour, which takes into consideration the hourly rate for a driver, an engineer, a brakeman, and an engine, which are \$100, \$100, \$100, and \$200, respectively. The *priority* service is 50% more expensive at \$750 per hour (Verma et al., 2012). Finally, we assume \$35,000 to the cost of terminal equipment.

3.2.2. Risk

Turning to the estimation of risk parameters, we focus on hazmat that become airborne in the event of an accidental release (such as chlorine, propane and ammonia) since they can travel long distances due to wind and expose large areas to health and environmental risks. Spatial distribution of toxic concentration level is estimated using Gaussian plume model (GPM), and at any given distance the maximum concentration is observed at the downwind locations (Arya, 1999). We use the immediately dangerous to life and health (IDLH) concentration levels of the hazmat being shipped in determining the threshold distances for fatality and injuries (http://www.cdc.gov/niosh). In estimating the population exposure, we adopt the worst-case approach by assuming least favorable weather conditions and focusing on maximum concentration levels (Verma and Verter, 2007).

We use the traditional bandwidth approach of Batta and Chiu (1988) and ReVelle et al. (1991) to assess population exposure risk for drayage and rail-haul. On the other hand, the congestion risk at the terminal was approximated via a circular impact area (Erkut and Verter, 1998) centered at the intermodal terminal.

3.3. Solution methodology

In the presence of nonlinear expressions in the risk objective and one of the constraints in (**P**), it is not possible to solve realistic-size problem instances through the general-purpose optimization software. Hence, we propose a customized solution methodology that exploits the problem structure, and label it RTIM-heuristic. The formal statement of the heuristic is presented in Fig. 2, which starts with the random generation of inbound traffic at each terminal in step 1. The resulting traffic is used as input in a multi-objective genetic algorithm, *viz.*, Non-dominated Sorting Genetic Algorithm (NSGA-II), to simulate a set of arrival rates for terminal equipment (Deb et al., 2002). Note that each simulated arrival rate (i.e., λ for regular and hazmat containers at both the origin and destination terminals) necessitates updating **(P)**, which in turn results in a linear model that could be solved using a standard optimization package. The aforementioned three steps (i.e., an iteration) are repeated until 500 consecutive iterations do not produce better solutions. We next discuss the main elements of the proposed heuristic.

Step 1 generates the input traffic at each intermodal terminal, by randomly selecting one of the available intermodal paths for each container going from a shipper to a receiver (i.e., OD pair). For instance, if the given container type (i.e., hazmat or regular) is sent on the 1st intermodal path, which goes through origin terminal A and destination terminal B – then the arrival rate at both terminals increase by one unit. This procedure is repeated until all the designated containers leave the shippers for one of the origin terminals, and the number at the corresponding destination terminal is adjusted based on the pre-processed intermodal paths.

The aggregate arrival at each terminal is to be distributed among different equipment, which is accomplished through random assignment. For instance, each container is randomly sent to an available crane (i.e., equipment) thereby reducing the remaining capacity of the said crane by one unit. It is important that an arrival rate of zero implies no crane purchase, and hence the total number of cranes purchased at a terminal would be equal to the number with arrival rates exceeding zero. Now in an effort to analytically investigate the trade-off between number of equipment and population exposure from congestion, we applied non-dominated sorting genetic algorithm. We next outline the implementation of this algorithm to evaluate the indicated trade-off.

In GA, including the non-dominated adaptations, 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 twice the number of equipment available for purchase in the given network (Fig. 3). We make use of a nonbinary encoding scheme to explicitly list the arrival rates for hazmat and regular containers for all equipment in a terminal. For example, λ_j^1

Step 1: Randomly generate input traffic at each terminal.
Step 2: Generate a set of solutions containing arrival rates at each equipment (NSGA II).

Initial Solutions

a) Randomly assign input traffic to available equipment & build chromosome.
b) Repeat until 100 chromosomes have been built.
   - Evaluate each chromosome "number of equipment" v/s "congestion exposure".
c) Selection and crossover.
   - Use binary-tournament selection method.
   - Use one-point crossover for generating offsprings.

Offsprings

d) Mutation operation on the offspring.
e) Evaluate the offspring through "number of equipment" v/s "congestion exposure".

Stopping Criteria

f) 1000 consecutive offsprings do not provide better solution.

Step 3: Update (P) and solve it using CPLEX
Step 4: Repeat steps 1, 2 and 3.
g) Until 500 consecutive iterations do not produce better solution.

Fig. 2. Summary of RTIM-heuristic.

Terminal *j*								*a*	*b*	*c*	Terminal *k*							
$\boldsymbol{\lambda_j^1}$	$\bar{\lambda}_j^1$	λ_j^2	$\bar{\lambda}_j^2$	..	..	λ_j^n	$\bar{\lambda}_j^n$	….	….	….	λ_k^1	$\bar{\lambda}_k^1$	λ_k^2	$\bar{\lambda}_k^2$	..	..	λ_k^n	$\bar{\lambda}_k^n$

Fig. 3. Encoding and chromosome.

	Terminal *j*						*a*	*b*	*c*	Terminal *k*					
Parent 1	8	7	6	10	5	6	….	….	….	2	3	5	6	9	11
Parent 2	12	5	7	6	0	12	….	….	….	0	3	5	9	12	7
Offspring 1	8	7	6	10	5	6	….	….	….	0	3	5	9	12	7
Offspring 2	12	5	7	6	0	12	….	….	….	2	3	5	6	9	11

Fig. 4. Crossover.

	Terminal *j*						*a*	*b*	*c*	Terminal *k*					
Parent	15	15	0	0	5	6	….	….	….	2	3	5	6	9	11
Offspring	6	8	10	6	4	7	….	….	….	2	3	5	6	9	11

Fig. 5. Mutation.

and $\bar{\lambda}_j^1$ are the arrival rates of hazmat and regular containers, respectively, at the 1st handling equipment in terminal *j*. The proposed encoding scheme adheres to three sets of constraints. *First*, the number of hazmat plus the number of regular containers arriving at each piece of equipment does not exceed its service rate (i.e., steady state condition). *Second*, the total number of containers (i.e., hazmat and regular) arriving at different equipment inside a terminal should be equal to the total input traffic generated in Step 1 of the RTIM-heuristic. *Third*, the waiting time of the containers inside any terminal is restricted to one hour. Finally, a repair technique is used to check each individual chromosome for violations. For example, if a container is waiting for more than an hour – another piece of equipment is added at that terminal. To sum, the input traffic generated for each terminal is randomly distributed among different equipment inside the terminal thereby generating one initial solution. The step entailing random distribution of the given input traffic is repeated until we have an initial population pool of 100.

A *binary-tournament* selection method was used to select parents, and in an effort to maintain diversity amongst the best solutions, the crowding distance comparison operator was implemented (Deb et al., 2002). Since crowding distance is a measure of the search space around a given solution that is not occupied by any other solution in the population, it ensures that chosen solution would lie on a better non-dominated front. Thus, the fitter of the two is retained, while the second parent is selected in the next iteration. The selected parents are subjected to a one-point crossover. For example in Fig. 4, the crossover operator is implemented starting at terminal *a*, and hence the relevant data is swapped between the two parents to produce the two offspring. Finally, an offspring is subjected to mutation with probability of 0.01. More specifically, for the selected offspring a terminal is randomly selected, and the number of available equipment is either increased or decreased – and then the input traffic is randomly re-assigned to those equipment. For instance, in Fig. 5, the two pieces of equipment at terminal *j* increases to three following mutation – thereby requiring the inbound traffic to be randomly assigned to the three pieces of equipment.

Each offspring is evaluated on the two conflicting objectives of number of equipment and population exposure from congestion, and the superior solutions replace the inferior ones in the population pool. This process continues until there is no improvement in 1000 consecutive offspring. Note that each such terminating solution will contain information about the number of equipment and the corresponding arrival rates (i.e., parameters and not decision variables), which in turn enables us to linearize the non-linear expressions in risk objective and constraint set (6) in **(P)**. Thus, knowing the arrival rate of each piece of equipment, **(P)** is updated and solved by CPLEX (IBM, 2014).

4. Computational experiments

Fig. 1 represent the intermodal train services of different types available for solving the realistic size problem instances, and is borrowed from Verma et al. (2012). The distinct demand data is randomly generated using the fuel oil consumption figures as compiled by the Department of Energy (http://www.eia.gov). It is important to note that no demand can be generated between a shipper and a receiver with access to the same terminal, since such movement will just use highway network and not a complete RTIM chain. Thus, we do not have a 37 × 36 demand matrix. It is assumed that each receiver specifies 42 h for shipment delivery. Finally, we assume that each crane (equipment) can service 96 containers a day, and a total of 120 cranes of identical types are available for possible acquisition at each terminal. The solution methodology was coded in C#, and numerical experiments were performed on Intel Core i5 CPU 1.80 GHz with 8 GB RAM.

4.1. Solution and discussion

Two of the most 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 attaches weights to different objectives. As indicated earlier, we pose the managerial problem from the perspective of the intermodal railroad operator, which is interested in minimizing total cost but is also under governmental pressure to consider public risk stemming from transport and congestion. Although we attach equal weights to both cost and risk objectives to solve the realistic size problem instances (hereafter referred to as the base case), we also report in Section 4.2 on a parametric analysis performed by attaching different weights to the two objectives.

Table 1 reports the objective function values for the base case solution, which was registered after evaluating over 50,000 offspring. The specified demand can be met by spending around $54.9 million, and by exposing just over 11.5 million individuals. Consistent with literature we notice that a significant proportion of both cost and risk accrued from drayage operations, but public risk stemming from congestion at terminals was not negligible and should be of interest to decision-makers. Note that this observation is incremental to and distinct from the study of Verma et al. (2012), which ignored congestion at terminals and focused on rail-haul operations.

In an effort to devote more space to the congestion issue, and also for exposition reasons, we only briefly discuss the rail-haul part of RTIM. It was noticed that 97 regular and 2 priority trains from the 31×2 available types were needed to satisfy network demand. The fixed cost of operating the 99 trains was $1,394,265 while container routing cost was $5,982,900, and 2,531,482 individuals were exposed. Finally, it was observed that Philadelphia, Atlanta and Charlotte were the busiest terminals, which in turn can be explained by the fact that twelve of the 31 train services originate at these yards, and another fourteen transit them.

Table 2 provides a snapshot of handling capacity and congestion at the terminals in the intermodal network depicted in Fig. 1. It is clear from the snapshot that Philadelphia has the highest congestion risk in the network, and one of the highest average waiting times for both hazmat and regular freight. This is interesting since a network maximum of 72 of the 120 available equipment (cranes) were acquired at this location, but the significantly higher input traffic precluded maximal risk reduction – perhaps because both cost and risk objectives were equally emphasized. Note that Chicago has the second high-

Table 1
Base case solution.

COST = $54,973,452			PUBLIC RISK = 11,503,674		
Rail-haul	Drayage	Acquisition	Rail-haul	Drayage	Congestion
7,377,165	31,916,288	15,680,000	2,531,482	6,365,150	2,607,042

Table 2
Capacity and congestion at terminals.

Terminals	Equipment/ Cranes		Congestion	Avg. waiting time (min)	
	Number	Cost ($)	Risk (people)	Hazmat	Regular
New York	4	140,000	306	12.53	55.91
Norfolk	8	280,000	3,690	15.32	51.85
Memphis	4	140,000	7,521	13.08	45.77
Jacksonville	11	385,000	13,162	15.12	53.21
Macon	5	175,000	13,584	17.13	51.76
Fort Wayne	8	280,000	24,122	16.57	54.63
Cincinnati	9	315,000	42,832	16.14	54.03
Roanoke	16	560,000	47,155	16.38	55.02
Cleveland	12	420,000	58,866	14.94	53.73
Detroit	10	350,000	63,841	15.98	53.41
Knoxville	26	910,000	66,521	17.19	57.40
Columbus	22	770,000	102,158	16.47	55.76
Indianapolis	39	1,365,000	106,797	16.40	56.85
Charlotte	50	1,750,000	146,652	16.09	55.91
Pittsburgh	24	840,000	167,612	16.46	56.26
Richmond	46	1,610,000	179,186	16.22	55.92
Atlanta	60	2,100,000	224,162	16.32	57.35
Chicago	22	770,000	285,347	15.69	55.54
Philadelphia	72	2,520,000	1,053,527	16.63	56.93
Total	448	$15,680,000	2,607,042		

Table 3
Cost-risk tradeoff.

Legends	Cost $ (millions)	Public Risk (people millions)			Cranes	Trains	
		Rail-haul	Drayage	Congestion		Regular	Priority
Min cost	54.108	2.751	10.169	2.541	446	95	2
$A = [c = 0.9, r = 0.1]$	54.356	2.615	8.024	2.587	450	95	2
$B = [c = 0.8, r = 0.2]$	54.403	2.577	7.276	2.598	448	96	2
$C = [c = 0.7, r = 0.3]$	54.609	2.543	7.110	2.609	452	96	2
$D = [c = 0.6, r = 0.4]$	54.889	2.537	6.651	2.589	452	96	2
Base case	54.973	2.531	6.365	2.607	448	97	2
$E = [c = 0.4, r = 0.6]$	55.553	2.500	5.928	2.596	448	98	2
$F = [c = 0.3, r = 0.7]$	56.048	2.481	5.720	2.583	451	99	3
$G = [c = 0.2, r = 0.8]$	56.523	2.478	5.575	2.575	451	101	3
$H = [c = 0.1, r = 0.9]$	56.866	2.473	5.490	2.597	448	100	4
$[c = 0.05, r = 0.95]$	64.767	2.490	5.466	1.966	671	103	3
Min risk	122.783	2.499	5.454	0.808	2280	116	12

est congestion risk, although the terminal is not as busy as the ones in Atlanta and Charlotte. This is because Chicago has a much higher population density, and hence exposes more individuals even when the transiting traffic is much lower than through the other two locations. Three observations can be made in this regard: *first*, these terminals are the major access points for the three regions, which is crucial information for designing intermodal networks; *second*, the expected risks at these terminals would the highest, which is a good surrogate measure to justify putting in place appropriate emergency response infrastructure; and *third*, effort should be made to mitigate risk at these terminals.

Note that the implementation of non-preemptive priority queuing principle resulted in significantly lower waiting times for hazmat traffic compared to regular traffic. This is important since most of the terminals are close to population centers in North America, and thus both the average waiting time and the number of hazmat containers waiting to be processed become critical in determining public risk. Hence, conceivably, any effort to lower the waiting time and number in the queue should reduce terminal risk. Based on our limited computational experiments, it seems that number of cranes (or employing faster equipment) would help. We investigate and comment on some factors affecting congestion in Section 4.2.2.

4.2. Managerial insights

In this section, we first comment on the impact of emphasizing one objective over the other, and then examine factors that affect terminal congestion. Furthermore, we examine the impact of changes in demand on the solution, and also investigate the application of the proposed framework to solve a tactical-operational planning problem.

4.2.1. Risk-cost tradeoff

We next report on the parametric analysis performed by varying the weights associated with the cost and public risk objectives in **(P)**, which were 0.5 in the base case. Each row in Table 3 (or each point in Fig. 6) represents a non-dominated solution, with the *min cost* and *min risk* constituting the two extremes. The *min cost* solution is 1.5% less expensive than the base case solution, but 34% more risky. The increment in risk is primarily stemming from forcing drayage operations through shorter but more risky paths, and partly from intermodal trains traveling on riskier routes. It is interesting to note that the congestion risk has decreased to around 2.541 million people from 2.607 million in the base case. On the other hand, the *min risk* solution is significantly more expensive because of the purchase of all the 120 available cranes at each of the 19 terminals and the larger number of priority trains, which collectively reduce the congestion risk by over two-thirds and the transport risk by just under a million.

It is important that ten of the eleven solutions are clustered around the *min cost*, which in turn signals the dominance of cost over public risk. To investigate this further, **(P)** was solved with five intermediate weight combinations between *H* and *min risk*. The decoded results revealed that the dominance of cost starts waning when risk has a weight of at least 0.95. For instance, with a weight of 0.05 on cost (highlighted in Table 3), the number of cranes purchased increased to 671 at a cost of $23.5 million versus 448 at $15.7 million in the base case (Table 2). This is important since, in this instance, attaching equal weight to the cost and public risk objectives is unlikely to provide a solution acceptable to both the regulatory agencies and the transport companies*.

It is easy to see from Table 3 (and Fig. 6) that the *min risk* solution entails a cost of around $122.8 million and exposes around 8.8 million people, whereas the *min cost* solution is the cheapest at $54.1 million but exposes around 15.5 million people. Although the exposure risk can be reduced by around 7 million if money is spent to purchase more cranes and move shipments on faster trains, this alternative may not be viable because of the significant amount of money required. Perhaps a

* **(P)** was rerun after scaling exposure risk at terminals, and distinct changes in routing was noticed. For example, some of the containers using Philadelphia now started going through New York –thereby having a commensurate impact on the number of intermodal trains originating and terminating at these terminals.

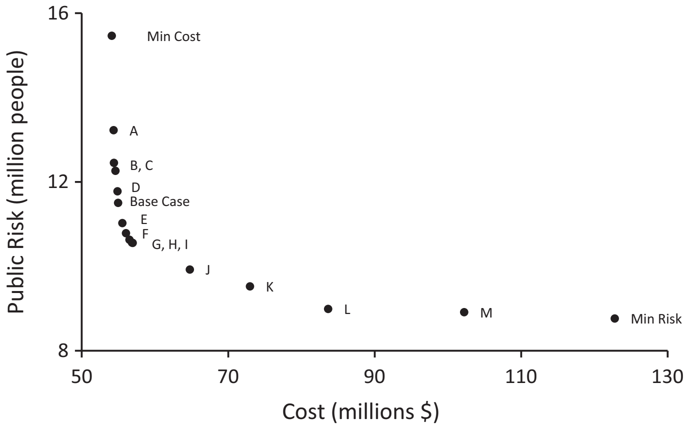

Fig. 6. Weight based solutions.

more worthwhile alternative to pursue could be to either encourage railroad companies to invest in or share the cost of purchasing 223 additional cranes (i.e., 671 versus 448). Doing so would entail a capital outlay of $8 million, but will decrease public risk by around 1.5 million people.

4.2.2. Factors impacting congestion risk

In this subsection, we throw light on some of the factors that could impact congestion risk at the intermodal terminals.

4.2.2.1. Utilization rate. It is evident from Table 3 that the number of cranes was a function of the weight being placed on the two objectives, since it had a direct bearing on congestion. In an effort to understand this behavior better, we focused on the operation of a single terminal. For exposition reasons we report only on Norfolk terminal, but note that similar patterns were observed at other terminals (see Table 4).

Note that emphasis on cost results in the purchase of fewer cranes, which in turn not only increases the utilization of the cranes to meet the same demand level but also results in higher average waiting time for hazmat containers. The last point leads to higher congestion risk. Hence, either purchasing more cranes or using better technology such that waiting times are reduced could be one of the ways to mitigate public risk at the terminals.

4.2.2.2. Delivery time. The base case delivery time of 42 h was varied by 6 h to investigate the impact on congestion risk. Delivery time of 36 h forced the purchase of more cranes and the use of a larger number of priority trains to move the shipments. More specifically, a total of 1873 cranes and 10 priority trains were used thereby increasing the equipment acquisition cost by around $50 million but decreasing congestion risk by 1.5 million people. On the other hand, a delivery time of 48 h returned a solution that was rather similar to the base case.

4.2.2.3. Waiting time. Recall that the maximum waiting time imposed in the base case was 1 h. Two additional waiting time instances, i.e., 3 h and 5 h, were also analyzed. In general, it was noticed that higher maximum waiting time resulted in fewer number of cranes being purchased, which in turn increased the average time being spent at the terminals. The latter of course resulted in higher congestion risk, but also necessitated using a larger number of priority trains to get shipments to their destinations before the expiration of the specified delivery times. For instance, the number of cranes decreased from 374 to 358 for the 3 h and 5 h instances, respectively. This change increased the congestion risk by 301 K people, and the number of priority trains by 3.

4.2.3. Change in demand level

In an effort to understand the impact of changes in demand on the solution, we experimented with two distinct increments in demand level: 10% and 20% (Table 5). Since higher demand meant moving more containers, both the cost and risk numbers increased. Furthermore, only the number of regular trains increased from 97 in the Base-Case to 112 and 121,

Table 4
Intermodal terminal at Norfolk.

	Cranes	Hazmat (min)	Congestion risk	Avg. utilization
Min cost	7	17.42	3705	0.75
Base case	8	15.32	3690	0.65
Min risk	120	0.80	171	0.05

Table 5
Impact of change in demand.

Demand level	COST ($ millions)			RISK (millions)		
	Rail	Drayage	Acquisition	Rail	Drayage	Terminal
Current	7.38	31.92	15.68	2.53	6.37	2.61
10% Increase	8.49	36.55	18.03	2.87	7.28	2.96
20% Increase	9.11	39.46	19.36	3.12	7.87	3.22

Table 6
Snapshot of the solution.

COST = $40,313,773			PUBLIC RISK = 10,535,547		
Rail-haul	Drayage	Operating	Rail-haul	Drayage	Congestion
7,366,429	31,939,344	1,008,000	2,524,395	6,361,071	1,650,081

respectively, for 10% and 20% instances. Finally, the number of cranes increased from 478 to 515 and 563, respectively, for the two increment levels. As expected, the entire demand is satisfied, although increased number of resources is being employed.

4.2.4. Tactical and operations application

Finally, we demonstrate the application of the proposed analytical framework to a tactical/operational setting. Under this scenario, the terminals in the network have a set of existing cranes, and the question is how many of them should be operational given the number of containers arriving at each terminal.

Note that under this setting crane operating cost of $1500, comprised of the maintenance and personnel costs, is being considered. For expositional reasons, and for brevity, we just report the solution wherein both cost and risk had equal weight (Table 6). It was interesting to note that while the number of trains needed to meet demand did not change from that reported in Table 3, the number of cranes increased by 50% (i.e., from 448 to 672). It is important to note that the larger number of (inexpensive) cranes being employed not only cost lower, but also has a positive bearing on risk.

5. Conclusion

In this paper, we propose a bi-objective optimization framework for planning rail–truck intermodal shipments, when terminal equipment capacity and congestion are considered. Congestion was captured by implementing a non-preemptive priority queue discipline on the containers arriving at various cranes (equipment), with higher priority being accorded to hazmat. The existence of non-linear terms in the risk objective and the constraints necessitated developing a customized solution methodology labeled *RTIM-heuristic* – that makes use of the attributes of genetic algorithm for multi-objective problems with CPLEX, which was applied to realistic size problem instances generated using the problem instance from existing literature.

Through extensive computational experiments, we conclude the following. *First*, congestion at the terminals is a non-negligible source of public risk, and could be a significant source if intermodal terminals are close to population centers. *Second*, terminal congestion risk can be mitigated using a variety of measures. For example, using better technology to process incoming hazmat containers would ensure lower transit time, which in turn has a positive bearing on risk. Alternatively, improving the processing times of cranes could also help mitigate risk, as would working with tight delivery times. Note that these findings are incremental to the ones reported in current literature (Verma and Verter, 2010; Verma et al., 2012; Xie et al., 2012).

Our contributions to the literature are threefold. *First*, this is the first work that incorporates congestion and equipment capacity decisions when planning rail–truck intermodal shipments of hazmat. *Second*, the dependence of congestion risk on the number of cranes (equipment), waiting time and delivery time are demonstrated. *Third*, this is the first application of a customized solution methodology that makes use of non-dominating sorting genetic algorithm and then the terminating solution attributes in CPLEX to build a cost-public risk frontier for planning rail–truck intermodal shipments. One of the limitations of the proposed work, i.e., Poisson arrival at destination terminals, was necessitated because of the absence of any comparable work and the inherent complexity of priority queues in a network setting is the immediate future research direction for this team. To that end, we would like to explore the impact of compound arrival Poisson process at a number of servers at a fixed location, and then extend the discussion to a network of interacting facilities. Terminal capacity is a function of a number of factors including the layout of transshipment tracks, which should be considered in the future models. Two other directions of future research include investigating the integration of terminal location decision with the routing decision, and the design of intermodal transportation networks in light of both hazmat and regular freight.

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