ANALYTICAL APPROACHES TO PLANNING INTERMODAL TRANSPORTATION SYSTEMS FOR REGULAR AND HAZMAT FREIGHT

by

© Ghazal Assadipour

A Dissertation Submitted to the

School of Graduate Studies

in Partial Fulfillment of the Requirements for the Degree of

Doctor of Philosophy

Faculty of Business Administration

Memorial University of Newfoundland

May 2014

St. John's Newfoundland and Labrador

ABSTRACT

The world container transportation industry has grown significantly over the past few decades. Large numbers of containers are transported everyday over long distances via a single or combinations of different modes of transportation (road, rail, water and air). Many of these containers contain hazardous materials (hazmat) whose transportation is regulated by governments due to the related risks. In contrast to other areas of transportation, operations-research-based models for intermodal transportation of containers, specifically hazmat ones, is still a young domain.

The purpose of the thesis is to provide analytical approaches to planning intermodal transportation for regular and hazmat freights. Planning of intermodal transportation can be addressed at the strategic, tactical or operational level. In this regard, this thesis contributes to the current literature in the following three ways. First, at the operational level, we study crane scheduling at an intermodal terminal, such that the unloading of inbound vessels and the loading of outbound vehicles could be completed in minimum weighted time. The approach calls for a multi-processor multi-stage scheduling methodology, where each crane has availability time windows. Second, at the tactical level, we propose a routing framework for transportation of hazmat and regular containers in a congested network to minimize two objectives: total cost and total risk. The model considers congestion as a source of exposure and makes a trade-off between congestion exposures and capacity costs. Third, at the strategic level, we study the regulation of intermodal transportation for hazardous materials. A bi-level network design model and a bi-level bi-objective toll-setting policy model, which consider government and carrier at two levels of administration, are proposed to mitigate the transportation risk.

The thesis concludes with comprehensive remarks. We summarize the contributions of this thesis, show the overall results obtained, and present the possible directions that this research may take in the future.

ACKNOWLEDGEMENTS

I would like to convey my utmost gratitude to Dr. Manish Verma and Dr. Ginger Ke, my thesis supervisors, for their unceasing guidance and support. I am indebted to Dr. Kara Arnold (Director, PhD program) for her persistent and kind support. I would also like to thank my thesis committee member, Dr. Dale Foster, for her feedbacks. Acknowledgement is also due to my mother and brother, for without their motivation and support none of this may have been possible.

DEDICATION

This thesis is dedicated to the memory of my father. It is his shining example that I try to emulate in all that I do.

Contents

LIST OF FIGURES

List of Tables

1. Introduction

1.1. Intermodal Transportation

Intermodal transportation can be defined as the synchronized sequential use of multiple modes of transportation (e.g., rail, truck and ocean shipping). It consists of a chain which links the initial shipper to the final receiver and takes place over long distances. An important component of this chain is the intermodal terminal, in which the mode of transportation changes and the freights are transferred from one mode to the next one using handling equipment.

As the principal part of intermodal transportation, container transportation has grown significantly over the past few decades. Higher cargo safety and accessibility to different modes of transportation, as well as the lower handling costs are the main reasons for containerization. According to United Nations Conference on Trade and Development (UNCTAD, 2012), world container throughput increased by an estimated 5.9 percent during 2011 to 572.8 million TEUs (twenty foot equivalent units), which was its highest level ever. Different modes of transportation (truck, rail, ocean shipping) are used to carry the containers from shippers to receivers.

In addition to the regular freights, large volumes of hazardous materials (hazmat) are transported through the intermodal networks every day. Hazmat (such as explosives, gases, flammable liquids) is harmful to health, safety and property, but their transportation is crucial for the industrial lifestyle. In 2009, Industry Canada indicated that about $40 billion of chemical products were shipped in Canada annually, representing more than 8% of all manufacturing shipments in the country (Transport Canada, 2011). Similarly in United States, 2.2 billion tons of hazardous materials, with the value of $1,448 billion, were transported in 2007 (US Commodity Flow Survey, 2007).

Planning of intermodal transportation can be addressed from strategic, tactical or operational levels. The strategic level decisions concern the design of the physical network, such as where to locate the terminals, and how much handling equipment to install at each terminal; while the tactical planning problems deal with optimally utilizing the given infrastructure, such as what routes to service, how to route the freights through the networks, and how to distribute the work amongst the terminals. Day to day decisions, such as fleet management and scheduling, are made at the operational level (Crainic and Kim, 2007).

Planning of intermodal transportation systems provides interesting areas in operations research and has gained more attention during the past decade. Crainic and Kim (2007), Christiansen et al. (2007) and Bektas and Crainic (2008) are the review papers and chapters emphasizing intermodal transportation problems. More recently, Steadieseifi et al. (2013) presented a structured overview of the multimodal transportation literature, focusing on the traditional strategic, tactical, and operational levels of planning. This thesis aims to provide analytical approaches for intermodal transportation of regular and hazmat freights at different levels of planning. The motivation and objectives of each approach are discussed in detail in the following section.

1.2. Motivation and Objectives

The importance of studying intermodal transportation planning problems is due to the fact that there are few accepted models and techniques. This is mainly because the research in this area requires a good knowledge of probabilistic programming in addition to optimization methods, specifically when it comes to hazmat transportation. Therefore, within this research, we focus on three important problems: one, crane scheduling at intermodal terminals; two, capacity planning and routing of containers considering the congestion; and three, regulating hazmat intermodal network.

At the operational level, we suggest a scheduling model for the sequencing of cranes at intermodal terminals. The trend towards container trade and larger container vessels has increased the demand for efficient terminal handling operations. How to achieve greater crane productivity becomes exceptionally important in improving port performance, in terms of shorter turnaround time of container ships, trucks and intermodal trains. A brief description of the problem is provided in section 1.3.1.

At the tactical level, we aim to develop a framework for capacity planning and routing of regular hazardous materials in congested networks. The hazmat transportation problems are highly uncertain in nature and involve multiple criteria, however there is no paper that takes uncertainty into account and considers multiple objectives. Particularly, the increasing risk of train disasters, because of the shipment of high concentrations of hazardous materials, calls for more research and exploration. Section 1.3.2 discusses the problem briefly.

Finally, at the strategic level, we wish to formulate models to regulate an intermodal network of hazmat. The importance of the problem is due to the mounting instances of hazmat derailments which necessitates a tighter regulation by the governments. Despite the exponential growth of hazmat shipments, the regulatory supervision and safety measures have not been updated very much. The problem is stated in more detail in section 1.3.3. The hierarchical relation among the three problems studied is presented in Figure 1-1.

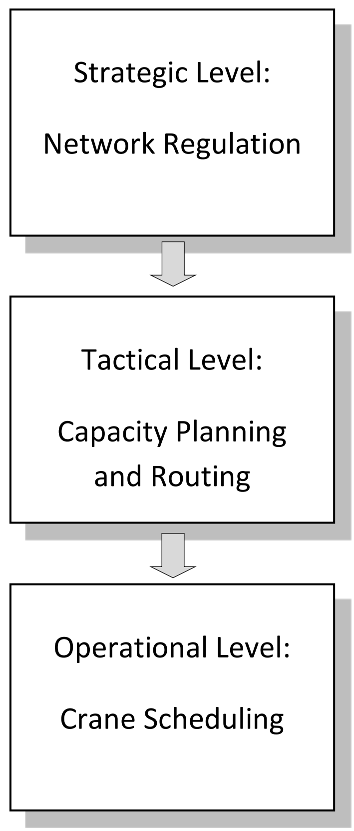


Figure 1-1: The relation between problems studied

1.2.1. Crane Scheduling at Intermodal Terminals

In the first contribution, we aim to improve the productivity of handling equipment (quay cranes and yard cranes) at container port terminals. Maritime container terminal handling operations can be divided into two parts: discharging or loading of containers from or onto a vessel, and transferring containers to or from outside trucks. Loading and unloading of containers into and from ships are provided by quay cranes, while yard cranes are used to transfer containers between stacks and outside trucks. Because of the high service cost of container ships, delays experienced at a port generate high costs (e.g. demurrage and wharf storage charges) to the ship's operators and final customers, and consequently lead to serious problems, such as high level of congestion and low shipping reliability (Crainic and Kim, 2007).

Chapter 2 aims to answer the research question: how to sequence the quay and yard cranes such that the total weighted completion time of unloading and loading containers at a terminal is minimized, where the cranes are not always available. To find the answer, a mixed integer programming model for scheduling cranes, in the presence of availability time-windows, is developed. Since there are two stages and each vehicle at each stage may require to be served by multiple cranes, the model combines multiprocessor task scheduling with cross-docking scheduling.

To solve the model, a genetic algorithm equipped with a novel decoding procedure is developed and tested by a series of problems generated based on the information of container ports. In addition, in an effort to demonstrate the effectiveness of the proposed meta-heuristic solution, we also provide results using another meta-heuristic technique: Elitist Evolutionary Strategy (EES). The computational results are compared and discussed. While Chapter 2 aims to schedule the cranes available at intermodal terminals, the capacity planning of those terminals, i.e. how many equipment items each terminal should choose, is the subject of Chapter 3.

1.2.2. Capacity Planning and Routing of Containers Considering the Congestion

In Chapter 3, we study the capacity planning and routing of regular and hazmat freights considering two criteria: cost and risk. More specifically, we consider a rail-truck intermodal network, where the containers are transported from shippers to receivers through drayage and rail segments. Transportation of containers from truck/train to train/truck is performed by handling equipment (e.g. cranes) at intermodal terminals. When the demand is uncertain, congestion may arise at those terminals.

In such a context, Chapter 3 seeks answers for the following three questions: 1) how many intermodal train services should be maintained? 2) How to route hazmat and regular containers to their destinations through the origin and destination terminals? and 3) What should the capacity of each intermodal terminal be with regard to congestion? To answer these questions, we propose a bi-objective nonlinear programming model for managing rail-truck intermodal transportation. The novel feature of the suggested model is the consideration of congestion as a source of exposure and delay when making equipment acquisition and routing decisions.

To solve the model, an iterative solution procedure incorporating a heuristic and a multi-objective genetic algorithm to generate a linear model that can be solved by CPLEX. A realistic problem instance is then employed to illustrate the practicality of the model.

This research helps decision makers identify the risky terminals and adopt appropriate reactive policies for risk management. To reduce the consequence of hazmat incidents *a priori*, proactive risk mitigation policies could be adopted. Chapter 3 focuses on the proactive policies regulating the use of intermodal terminals by hazmat carriers.

1.2.3. Regulating Hazmat Intermodal Network

Chapter 4 studies the regulation of a rail-truck intermodal network of hazardous materials, where the government controls the network to mitigate the transportation risk, and the carrier determines the routing of shipments. Unlike Chapter 3, which considers only one decision maker, here we (realistically) assume that there are two decision makers (government and carrier) at two levels of administration. The decision makers make their decisions sequentially, i.e. the government executes its decision prior to the carrier. More specifically, the government prohibits the carrier's choice of certain terminal(s) by applying network design and toll policies.

Based upon the hierarchical decision-making, Chapter 4 aims to answer the following question at the upper level (government):

How to choose the terminals to be closed for hazmat transportation, and how to use tolls in the toll setting policy, to minimize the population exposure?

And, to answer the following two questions at the lower level (carrier):

What is the best shipment plan for both hazardous and regular freights in an RTIM network, such that total transportation cost is minimized?

To answer the questions, we formulate two bi-level models for the network design and toll setting policies. The main contributions of Chapter 4 are considering an intermodal network, combining location and routing model development and comparing two regulating policies. The models are solved using a single objective and a multi-objective Particle Swarm Optimization (PSO).

1.3. Co-authorship Statement

I, Ghazal Assadipour, hold a principal author status for all the manuscript chapters (Chapter 2-4) in my thesis. However, each of the manuscripts is co-authored by my supervisors, Dr. Manish Verma and Dr. Ginger Y. Ke, whose contributions have greatly facilitated the development of the ideas in the manuscripts, the practical aspects of the computational experiments and the manuscript writing. The contributions, for each manuscript, are listed in the followings:

Manuscript 1, "An analytical framework for integrated maritime terminal scheduling problems with time windows":

Located in chapter 2

- Presented at INFORMS 2013, Minneapolis, US
- Presented at CORS 2014, Ottawa, Canada
- Accepted for publication in the ISERC 2014 proceedings, Montreal, Canada

- Accepted for publication in Expert Systems with Applications

Manuscript 2, “Planning and managing intermodal transportation of hazardous materials with capacity selection and congestion”:

Located in chapter 3

- Winner of the second place in a worldwide interactive poster competition at INFORMS 2013, Minneapolis, US
- Accepted for presentation at CORS 2014, Ottawa, Canada
- Selected to be one of the 5 finalists of the student paper competition at CORS 2014, Ottawa, Canada
- Under 2nd review at Transportation Research Part E

Manuscript 3, “Regulating Intermodal Transportation of Hazardous Materials”:

Located in chapter 4

- Accepted for presentation at CORS 2014, Ottawa, Canada
- Accepted for presentation at IFORS 2014, Barcelona, Spain
- Accepted for presentation at INFORMS 2014, San Francisco, US
- To be submitted

1.4. Organization of the Thesis

Figure 1-2 outlines the organization of this thesis. Chapter 1 began with a brief introduction of this research, including problem statement, motivation and objectives, and finally the co-authorship statement. Then the focal research was classified into three models, which study three problems related to different levels of planning. Chapters 2 through 4 report our research contributions. Three problems related to the operational, tactical and strategic level of planning are investigated and applied to real problem instances. Finally, Chapter 5 reemphasizes the finding of this research and summarizes the work that we have done and drafts a blueprint for future research.

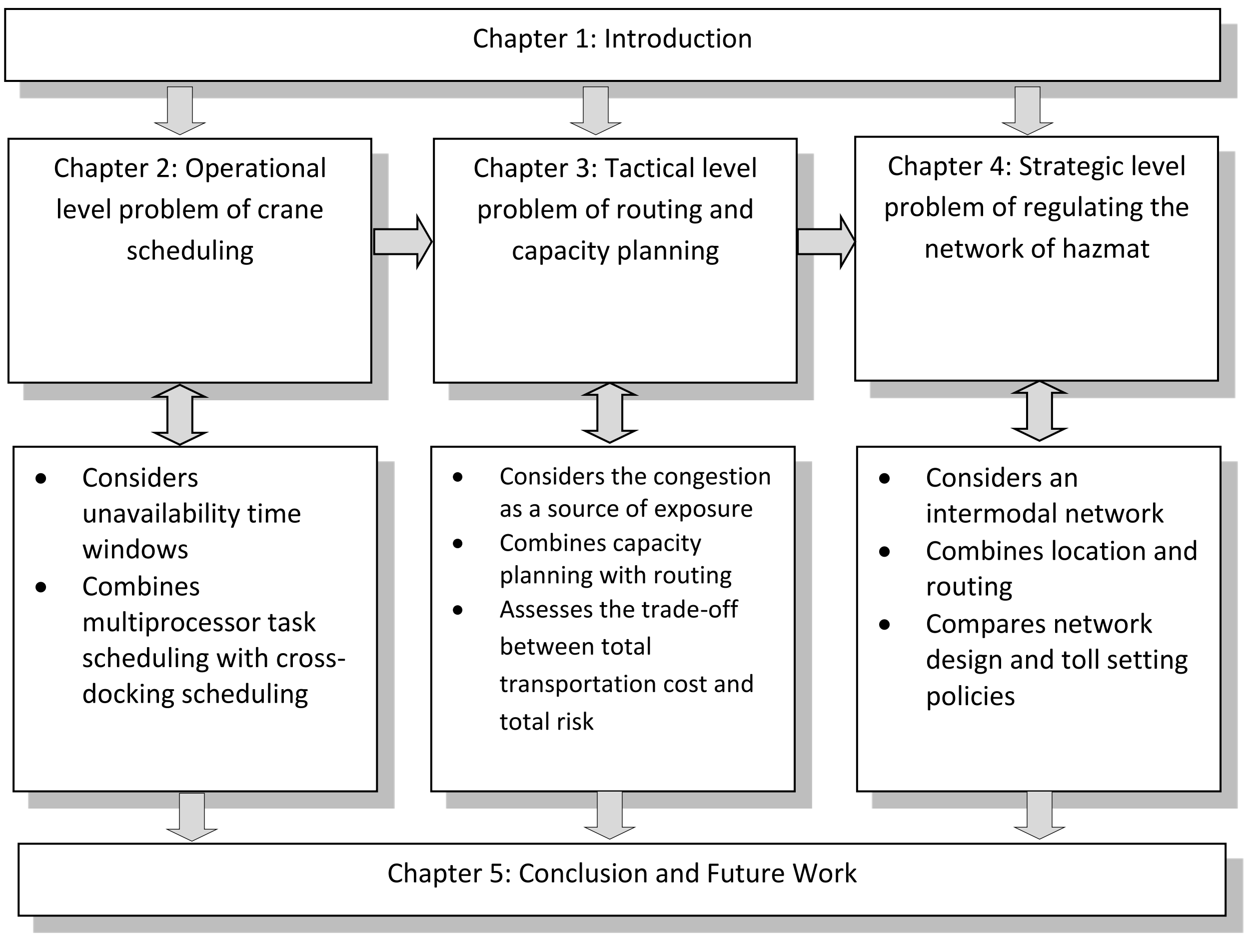


Figure 1-2: Organization of the thesis

2. An Analytical Framework for Integrated Maritime Terminal Scheduling Problems with Time Windows

Abstract: This research studies the sequencing of quay and yard cranes to minimize the total weighted completion time of unloading and loading containers at a terminal. A mixed integer programming model is developed in considering multiple cranes, each with its individual time windows, in the two stages. A meta-heuristic approach is designed and implemented to solve the proposed model. Detailed computational tests illustrate the applicability and effectiveness of this study.

Keywords: container transport; maritime terminal; crane scheduling; genetic algorithm.

2.1. Introduction

Intercontinental trade, primarily conducted through container transport on ships, has steadily grown in size over the past few decades. In 2013, global container trade is projected to grow by 5 per cent, and global container supply, by 6 per cent (UNCTAD, 2013). In line with the increasing global trend, around 45mn containers were handled by the major ports in North America (Colliers, 2012). The statistic was equally impressive for Canadian ports, which collectively handled 4.8mn containers in 2010, almost a two-third increase from the volume a decade ago (CIY, 2012). For example, the port of Montreal processed around 1.4mn containers in 2011, which showed a 34 percent increase over the volume in 2000. The increased need for outsourcing and the existence of supply chain partners in different parts of the world imply continued reliance on intercontinental trade (and container transport), and calls for effective allocation of resources to both improve the lead-time and also make the chain more competitive. Efficient operations in a marine terminal, one of the transshipment points in intercontinental freight movement, are crucial to realizing the two objectives.

Marine container terminal operations can be broadly divided into container loading/unloading performed by quay cranes and yard cranes, where the former attend to the ships, and the latter is responsible for moving containers from dockside stacks (storage) to the intermodal trains and trucks. Note that any port related delays could entail much higher costs for the container ship operators and the final customers, not to mention the unanticipated congestion at the terminal and the associated questions about reliability (Crainic and Kim, 2007). It should be clear that the efficient allocation of the two types of cranes could significantly impact the turnaround time (the time spent to make a transport vehicle ready for departure after its arrival) of container ships, trucks and intermodal trains, thereby improving port productivity, primarily achieved through increased container throughput and/or decreased processing time.

This chapter investigates the scheduling of quay cranes for seaside and yard cranes for landside operations, and proposes a two-stage multi-processor scheduling model with time windows (TMSTW). More specifically, in the first stage, containers from n_1 ships are unloaded by m_1 quay cranes and stacked. Each quay crane is available in certain time windows during the twenty-four hour period, and is offline for maintenance the remaining time. For this stage, a job is defined as the unloading of all containers from a berthed ship.

In the second stage, the unloaded containers would be retrieved from the temporary stacks (storage) by m_2 yard cranes, and placed on the intermodal trains and trucks to be transported to n_2 customers. Since more than one container may be destined to a single customer, a job in the second stage is defined as the loading of all containers belonging to one shipment. Finally, each yard crane has an availability time window, and the loading operation can start only after the unloading of the relevant containers from the ship. Hence, the objective of this study is to schedule the operations in the two stages so that the (total) weighted completion time is minimized.

The rest of this chapter is organized as follows. Section 2.2 reviews the related research, while a formal problem definition is outlined in Section 2.3. Section 2.4 outlines the sets and indices before presenting the mixed-integer programming model, which is NP-hard. Section 2.5 develops a genetic algorithm, equipped with a novel decoding procedure, to solve the proposed model. Section 2.6 discusses the results and analysis of numerous problem instances of varying size, and compares the performance of the proposed solution technique with another meta-heuristic technique. Finally, Section 2.7 contains the conclusion and highlights the contribution of the proposed work.

2.2. Literature Review

The relevant literature can be organized under three threads: seaside, landside, and integrated operations. One issue of the seaside operation is quay crane scheduling problem that deals with determining the service sequence for each crane, and the associated schedule. Tasks in the crane scheduling problem are defined based on single bays (one quay crane serves a particular bay), or container groups (the cranes can share the workload of bays) (Bierwirth and Meisel (2010)). Daganzo (1989), one of the first studies in the group of single bays, assumed that ships are divided into holds (a ship's hold is a space for carrying cargo), and only one crane can work on a hold at a time. The paper developed solution methods for both dynamic and static schedules, such that the aggregate cost of delay is minimized. Subsequently, Peterkofsky and Daganzo (1990) considered the problem as an open shop scheduling problem with parallel and identical machines, where jobs consist of independent single-stage preemptable tasks (running job can be interrupted for some time and resumed later). They developed a branch and bound algorithm for the static crane scheduling problem, such that the cost incurred by ships at the port was minimized. More recently, Lee et al. (2008a) provided a model to determine a handling sequence of holds for quay cranes assigned to a container vessel, considering interference between quay cranes, i.e., a crane cannot overreach any other cranes because they are on the same track. A genetic algorithm was employed to solve the model. The same authors (Lee et al., 2008b) studied another quay crane scheduling problem, which considers the handling priority of every ship bay, and also solved it using a genetic algorithm.

In the second class of papers the task is defined based on container groups, Kim and Park (2004) modeled a quay crane scheduling problem, assuming that there may be multiple tasks involved in a ship-bay, and thus, a task is divided into smaller sizes. To minimize the makespan, they proposed a heuristic search algorithm to find near optimal solutions. More recently, Bierwirth and Meisel (2009) considered the quay crane scheduling problem with container groups that can be assigned to different quay cranes. Taking crane interference into account, they developed a mixed integer model and then solved it using a heuristic procedure with a branch-and-bound algorithm at its core for searching a subset of above average quality schedules. Kaveshgar et al. (2012) designed a genetic algorithm to solve a quay crane scheduling problem which minimizes the summation of makespan and completion time of each quay crane. Quay cranes in this study are allowed to move in a different direction, independent of one another. Chung and Choy (2012) also proposed a genetic algorithm for a similar problem; however the applied components, such as chromosome representation and fitness evaluation, were different. Considering congestions in the yard, Jung et al. (2006) proposed a heuristic search algorithm to construct a schedule for quay cranes, so that the makespan is minimized. They considered a time window for each crane, but did not delineate it in detail. Assuming cranes can be temporarily removed from a vessel during the service, Meisel (2011) developed a mixed integer model for scheduling of cranes on the basis of container groups. They revised the heuristic suggested by Bierwirth and Meisel (2009) to solve the model. Legato et al. (2012) studied independent unidirectional quay crane scheduling under time windows, and unlike Bierwirth and Meisel (2009), assumed that cranes can move in different directions. They solved the model by a branch and bound method. Please note that the literature related to other seaside operations, such as berth allocation and stowage planning, are not addressed here because the focus of this research is on the integration of operations as a whole in cross docking scheduling rather than the berth planning and operations inside the terminal. For comprehensive overviews on the quay crane scheduling, we invite readers to refer to Bierwirth and Meisel (2010) and Carlo et al. (2013).

The yard crane scheduling problem entails removing containers from storage (or temporary stacks) and loading them onto the flatbed of the intermodal trains and trucks on the landside. Kim and Kim (2003) studied the routing of yard equipment during loading operations, such that the total container handling time in a yard is minimized. The proposed model was solved using both genetic and beam search algorithms. Li et al. (2009) developed a model for yard crane scheduling, which considered crane interference and separation distances, as well as simultaneous storage/retrievals. The resulting model was solved by a rolling horizon heuristic. Most recently, Chen and Langevin (2011) developed a mixed integer programming model to solve the multi-crane scheduling problem. The proposed model determined the movement of yard cranes among container blocks, and the sequence for the cranes within each block. Both genetic algorithm and tabu search based meta-heuristic solution techniques were proposed.

Finally, the integration of seaside and landside operations has been studied by a few researchers. Chen et al. (2007) investigated the scheduling of different types of terminal equipment, such as quay cranes, yard cranes, and yard vehicles. A hybrid flow shop scheduling approach with precedence and blocking constraints was used to formulate the problem, which was solved using a tabu search solution technique. On the other hand, Chen and Lee (2009) attempted to minimize the makespan involving unpacking operations of inbound carriers and collection operations of outbound carriers. The problem was formulated as a cross docking flow shop problem, in which there were exactly two stages with one machine and a set of jobs in each stage. It was assumed that jobs in the second stage can be processed only after all their corresponding precedent jobs have been completed in the first stage. This model was extended by Chen and Song (2009), who considered the problem with more than one parallel machine in at least one of the two stages.

The model we study in Chapter 2, like the cross dock scheduling problem discussed above, examines a two-stage problem with precedence constraints. However, two distinct characteristics make our model unique from the previous studies. First, multiple cranes with their own availability time windows are available in each stage. As indicated earlier, these time windows enable us to incorporate unavailability, which could be for maintenance, adherence to labor regulations, and so on. Second, our model allows multiprocessor tasks, i.e., each job may require several cranes simultaneously. To the best of our knowledge, Guan et al. (2002) is the only study that considered the multiprocessor scheduling problem in container terminals. The authors investigated the ship berth allocation problem where the objective was to minimize the total weighted completion time of ships. The model proposed in Chapter 2 is distinct from earlier studies, since it considers both time windows and multi-processors in both stages to investigate the scheduling of cranes in a marine terminal. More specifically, the goal of our model is to schedule the quay cranes to unload inbound ships and the yard cranes to load outbound intermodal trains and trucks.

However we have considered container port terminals as the context of our first study, scheduling of key resources is an issue in all types of intermodal terminals and our developed approach can be applied to other transportation modes too.

2.3. Problem Statement

The proposed model focuses on the terminal level operations and seeks to answer the following question: what is the most efficient way to schedule a given set of quay cranes on the berthed vessels and the yard cranes to load the containers for outbound movement, such that the total weighted completion time is minimized?

To make this explicit, consider a marine terminal in which four container ships are berthed concurrently, waiting to be unloaded. There are four jobs in the first stage, and each job has three attributes: processing time, required number of cranes, and priority (or weight). Furthermore, let us assume that the unloaded containers have to be loaded on trucks and intermodal trains for outbound movement to six different destinations. Finally, the loading of containers cannot start until all the predecessor jobs are completed. For example, loading of containers for destination *5* cannot be started before both vessels *1* and *2* have been completely unloaded (Table 2-1). Table 2-2 depicts the number of cranes in each stage, and their respective availabilities. For example, assuming a 24 hour clock, the fifth yard crane (i.e., *YC5*) is not available until 8 am in the morning, and then again from 4 pm to midnight. On the other hand, there is no maintenance or scheduled breaks for *YC1* and *YC4*.

Table 2-1: Jobs and relevant attributes

Stage	Vessels/ Destinations	Processing time (hour)	Number of cranes	Priority	Predecessors
1st	*1*	2	3	1	
	2	5	2	1	
	3	4	2	1	
	4	2	3	1	
2nd	*5*	2	2	1	{1, 2}
	6	3	1	1	{1, 2}
	7	2	2	1	{3}
	8	1	3	1	{3}
	9	2	2	1	{4}
	10	2	2	1	{4}

Table 2-2: Availability time window for cranes

Stage	Cranes	From	To
1st	*QC1*	0	5
		10	24
	QC2	0	10
		15	24
	QC3	0	15
	QC4	5	24
2nd	*YC1*	0	24
	YC2	0	8
		16	24
	YC3	0	16
	YC4	0	24
	YC5	8	16

Figure 2-1 depicts a feasible schedule for the nine machines. Each machine is used only during the available time windows (shaded areas illustrate the unavailable periods). For example, vessels *1* and *4* require three quay cranes each; and the first three quay cranes are available until 5 am, and hence can be employed concurrently to unload each of the two vessels. In the 2^{nd} stage, we have to consider the predecessor constraints, and hence loading for destinations *9* and *10* can start as soon as vessel *4* has been unloaded. On the other hand, loading for destinations *5* and *6* cannot start even if vessel *1* has been unloaded, since vessel *2* is not unloaded until 1 pm (i.e., end of the 13th hour). As such, other completion times can be interpreted similarly. The total completion time for this schedule is 86 hours.

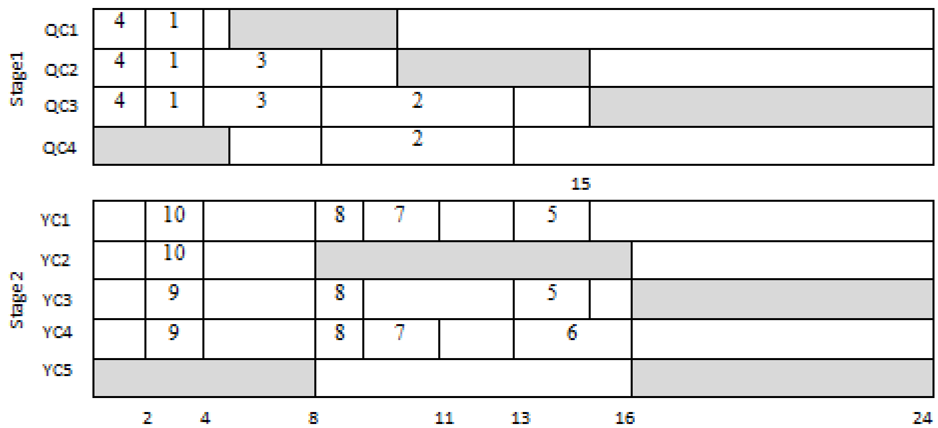


Figure 2-1: A scheduling plan for the jobs of the same priority

Note that the priority of a job, which is determined by the freight type, due date, and so on, affects the entire sequencing, given the available resources. To show the effect of the jobs' priority on the scheduling plan, we present another feasible schedule (Figure 2-2), in which jobs *3*, *7* and *8* have higher priority and need to be processed as early as possible. We can see from the figure that, under this circumstance, the sequence of jobs is rearranged according to the priority, but the total completion time increases to 105 hours. In the next section, we develop a mixed-integer program to tackle realistic size managerial problems as outlined above, so that the total weighted completion time is minimized.

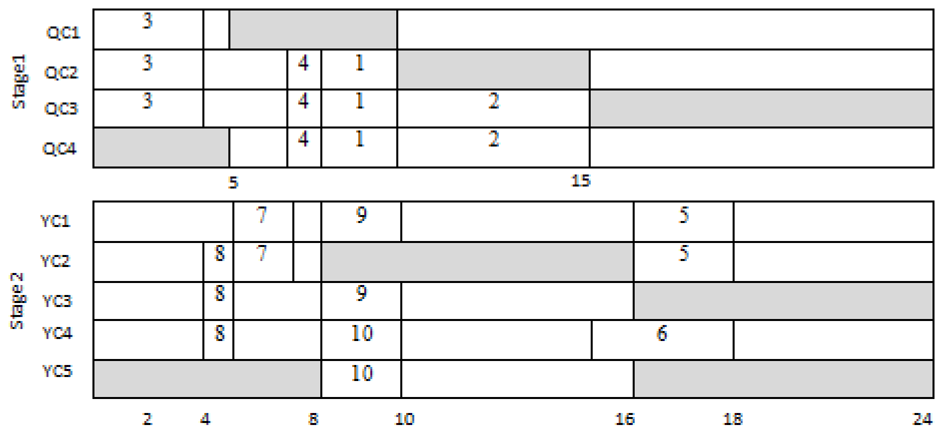


Figure 2-2: A scheduling plan where jobs are of different priorities

2.4. Mathematical Model

This section outlines major assumptions behind the proposed TMSTW problem, and then develops the mathematical formulation. There are seven major assumptions: *first*, pre-emption of jobs is not permitted. i.e., a running job cannot be interrupted until its completion; *second*, each job is processed simultaneously by the required number of cranes; *third*, the number of jobs, their processing times, weights and the required number of cranes at each stage are given; *fourth*, there are only two stages, and the number of cranes in each stage is given; *fifth*, each job in the second stage can start only after the completion of the precedent jobs in the first stage; *sixth*, for each crane in each stage a set of availability time windows is given; and finally, because this study focuses on operations as a whole in cross docking scheduling, additional crane's attributes, such as interference between cranes, are not considered here. We next define the sets, parameters and variables for the mathematical model.

Sets

I Set of stages, indexed by *i*.

V_i Set of cranes in stage i, indexed by $v = \{1,2, \dots, m_i\}$.

J_i Set of jobs in stage i, indexed by $j = \{1,2, \dots, n_i\}$.

T_{iv} Set of availability time windows for crane *v* in stage *i*, indexed by $u = \{1,2, \dots, k_{iv}\}$.

S_j Set of precedent jobs in J_1 for job *j* in stage 2, indexed by *s*.

Decision Variables

C_{ij} Completion time of job *j* in stage *i*.

X_{ivj}^{u} $\begin{cases} 1, \text{ if job } j \text{ is assigned to the time window u of crane } v \text{ in stage } i \\ 0 \text{ otherwise} \end{cases}$

Z_{ijf} $\begin{cases} 1, \text{ if job } j \text{ precedes job f in stage } i \\ 0 \text{ otherwise} \end{cases}$

Parameters

Q A large positive integer.

P_{ij} Processing time of job *j* in stage *i*.

W_{ij} Weight of job *j* in stage *i*.

Y_{ij} Size of job *j* in stage *i* (i.e., number of cranes required).

D_{iv}^{u} End of time window *u* for crane *v* in stage *i*.

R_{iv}^{u} Start of time window *u* for crane *v* in stage *i*.

m_i Number of cranes at stage *i*

n_i Number of jobs at stage i

k_{iv} Number of available time windows for crane v at stage i

TMSTW

$$Min\ \sum_{i\in I}\sum_{j\in J_i} W_{ij}C_{ij} \tag{2-1}$$

Subject to

$$\sum_{v\in V_i}\sum_{u\in T_{iv}} X_{ivj}^u = Y_{ij} \qquad i\in I, j\in J_i \tag{2-2}$$

$$\sum_{u\in T_{iv}} X_{ivj}^u \le 1 \qquad i\in I, j\in J_i, v\in V_i \tag{2-3}$$

$$C_{1j} \ge P_{1j} \qquad j\in J_1 \tag{2-4}$$

$$C_{2j} \ge C_{1s} + P_{2j} \qquad j\in J_2, s\in S_j \tag{2-5}$$

$$C_{ij} \le Q\left(1 - X_{ivj}^u\right) + D_{iv}^u \qquad i\in I, j\in J_i, v\in V_i, u\in T_{iv} \tag{2-6}$$

$$C_{ij} - P_{ij} \ge\ X_{ivj}^u R_{iv}^u \qquad i\in I, j\in J_i, v\in V_i, u\in T_{iv} \tag{2-7}$$

$$C_{ij} + Q\left(2 + Z_{ijf} - X_{ivj}^u - X_{ivf}^u\right) \ge C_{if} + P_{ij}$$

$$i\in I, j\in J_i, f\in J_i, v\in V_i, u\in T_{iv} \tag{2-8}$$

$$C_{if} + Q\left(3 - Z_{ijf} - X_{ivj}^u - X_{ivf}^u\right) \ge C_{ij} + P_{if}$$

$$i\in I, j\in J_i, f\in J_i, v\in V_i, u\in T_{iv} \tag{2-9}$$

$$Z_{ijf} + Z_{ifj} = 1 \qquad i\in I, j\in J_i, f\in J_i \tag{2-10}$$

$$X_{ivj}^u \in \{0,1\} \qquad i\in I, j\in J_i, v\in V_i, u\in T_{iv} \tag{2-11}$$

$$Z_{ijf} \in \{0,1\} \qquad i\in I, j\in J_i, f\in J_i \tag{2-12}$$

C_{ij} is a positive number $\qquad i\in I, j\in J_i$ (2-13)

TMSTW is a mixed integer programming model, where (2-1) aims to minimize the weighted completion time of all jobs. The job weight is a subjective or objective attribute, which is determined by the decision maker to represent the priority of each job. Constraint set (2-2) ensures that, in each stage, each job is assigned to exactly the required number of cranes. Constraint set (2-3) guarantees that each job is performed in at most one time window of a crane. Constraint set (2-4) shows that each job is processed in the first stage, while (2-5) makes sure that precedence requirements are met. For example, job *j* in the second stage will start only after completing all the precedent jobs in the first stage, which are contained in set S_j. Constraints (2-6) and (2-7) ensure that each job is both started and finished within the available time windows i.e. the jobs would be assigned to cranes only if they could be started and finished within the respective time windows. The next three constraint sets indicate that no two jobs can be processed on the same crane simultaneously. For any given sequence of jobs, either (2-8) or (2-9) is active. For example, if job *j* is processed earlier than job *f* on the same crane, we have $Z_{ijf} = 1$, $C_{if} \geq C_{ij} + P_{if}$, and $X^{u}_{ivj} = X^{u}_{ivf} = 1$. Furthermore, constraint set (2-10), together with (2-8) and (2-9), ensures that only one of the two jobs can be processed in that time window by a given crane. Constraint sets (2-11)-(2-13) represent the sign restrictions on the decision variables.

2.5. Solution Method

If the size of each job in the first and the second stage is 1 and the cranes are always available, then TMSTW will lead to the two-stage hybrid cross docking scheduling problem. Since two-stage hybrid cross docking scheduling problem has been shown to be NP-hard by Chen and Song (2009), it is not difficult to see that TMSTW is NP-hard too and cannot be solved completely and exactly within tolerable resource bounds using common optimization software.

Since TMSTW typically contains a huge number of variables and relatively fewer constraints, a genetic algorithm (GA) based solution methodology would be effective and efficient (Holland, 1975). Moreover, GA has been successfully applied to many combinatorial optimization problems.

2.5.1. Chromosome Coding and Decoding

In GA, a proposed solution is defined as a set of values represented as a simple string called a chromosome (or genome). Given the nature of TMSTW, we determine the length of the chromosome by the number of jobs and use a non-binary encoding scheme. For example, consider the illustrative case in Section 2.3, Figure 2-3 shows a sample chromosome.

4	1	3	2	10	9	8	7	6	5

Figure 2-3: A sample chromosome

Please note that, by our definition, we do not require the first-stage jobs to be listed before those in the second stage. In fact, when a second-stage job shows beforehand, the chromosome is repaired and thus its validity is maintained. Consider an initial chromosome of {10, 4, 9, 1, 3, 2, 8, 7, 5, 6} and assume that jobs 1 to 4 and jobs 5 to 10 belong to the first and second stages respectively. Since jobs belonging to the second stage precede those in the first stage (for example job 10 precedes job 4 in the chromosome), the chromosome needs to be repaired. Through a repair mechanism, jobs {4, 1, 3, 2} are brought prior to {10, 9, 8, 7, 5, 6}. The repaired chromosome would be {4, 1, 3, 2, 10, 9, 8, 7, 5, 6}. It should also be emphasized that the repair mechanism preserves the order of the jobs within each stage, and only shifts those belonging to the first stage to the left. The repair is performed at the beginning of a decoding procedure that is presented next.

To decode the chromosome, we propose a unique decoding procedure, which derives the individual completion time for each job as well as the total completion time. The developed decoding procedure converts each chromosome to a full schedule by iteratively assigning the jobs to the cranes in their order in the chromosome. It is important to note that, the feasibility of a solution is preserved during the process. More specifically to conserve the precedence constraint (constraint 2-5), the procedure first assigns the jobs in the first stage and computes their completion times. For a job in the second stage, the procedure considers the completion time of its predecessors in the first stage (assumption 5 in Section 2.4). In other words, the starting time of a job in the second stage cannot be less than the maximum completion times of its predecessors in the first stage. To preserve the resource availability constraint (constraints 2-2, 2-6 and 2-7) when assigning a job, the procedure checks if an adequate number of cranes is available to serve. Figure 2-4 presents the decoding flowchart. To have a better understanding of how this procedure works, we outline it for the given chromosome.

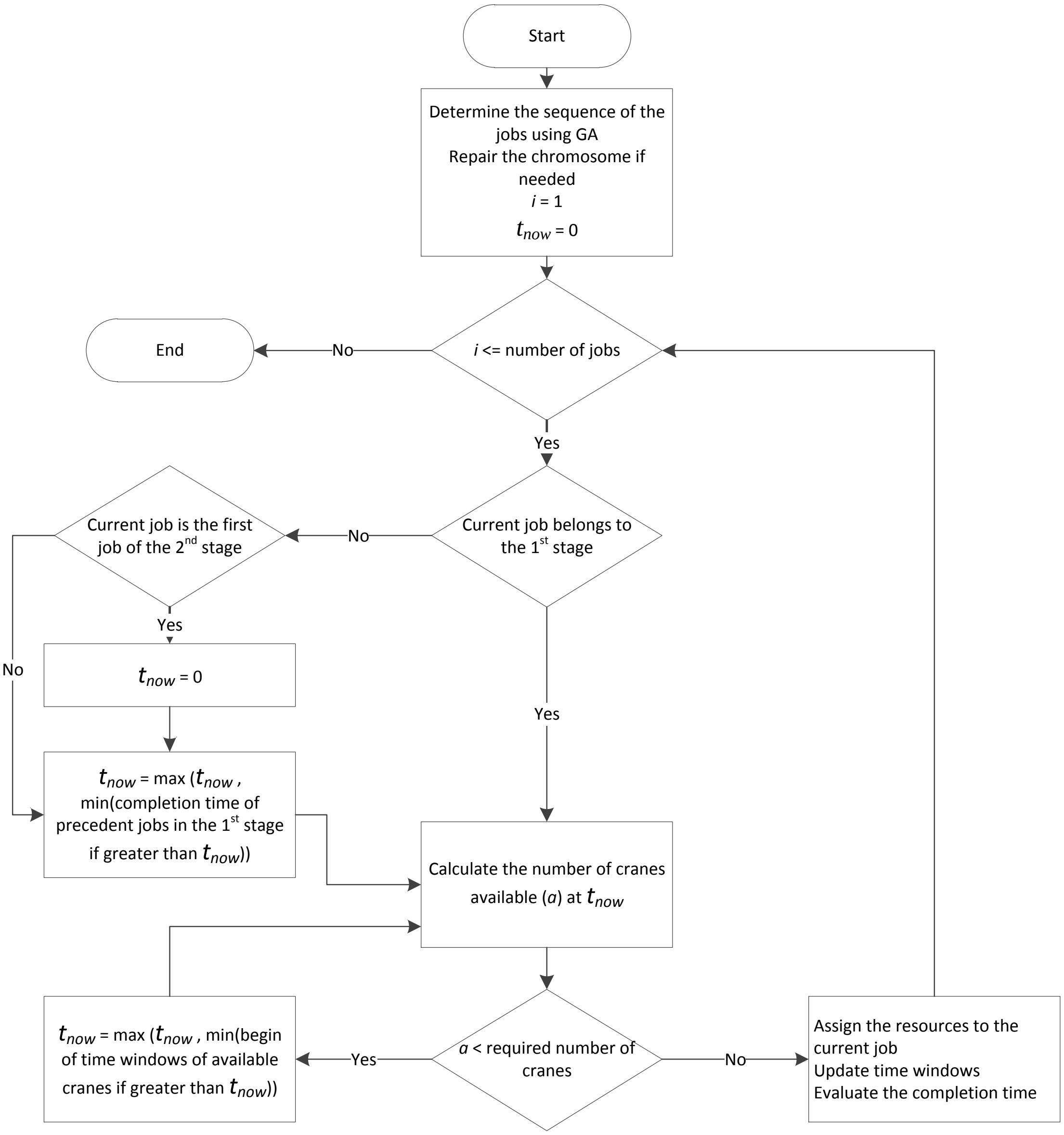


Figure 2-4: Decoding flowchart

In the 1st stage, the current time (i.e., t_{now} is set to 0, and the number of available resources are determined. Recall from Section 3 (Table 2-2) that 3 quay cranes are available for the first 5 hours, and hence all of them could be assigned to vessel 4 that needs 3 cranes for 2 hours. Since vessel 4 would be completely unloaded at the end of hour 2, the availability of each crane is updated accordingly. For example, *QC1* will now be available at the beginning of hour 2 and until the end of hour 5 (i.e., [2-5]). The next vessel is 1, which also requires 3 quay cranes for 2 hours. Note that the number of quay cranes at t_{now} = 0 is not enough to service 1, and hence the procedure updates t_{now} to the maximum of current t_{now} and the minimum of the beginning of the earliest time window for all quay cranes if greater than t_{now}. More explicitly, the updated t_{now} = max {0, min (2, 2, 2, 5)} = 2, where the four elements inside the inner parenthesis represent the availabilities of the four quay cranes after completing unloading vessel 4 and are all greater than t_{now}. Note that *QC4* is never used to service 4; it is unavailable until the end of hour 5. Since there are adequate numbers of cranes available at the end of hour 2, vessel 1 could be serviced in hours 3 and 4.

Now consider a different case: vessel 1 requires 4 quay cranes instead of 3, and *QC1* is always available. The steps will be as follows: after updating t_{now} to 2, since there are only 3 quay canes available, vessel 1 cannot be served. Thus t_{now} is updated again: t_{now} = max {2, min (24, 15, 24, 5)} = 5, where 24, 15 24, 5 are respectively the beginnings of the next time windows of all the cranes. Because quay crane 1 and 3 have only one time window, the beginning of their next time window is set to 24 (the maximum value possible). This procedure continues until all the jobs have been scheduled.

Scheduling in the 2nd stage is similar to what discussed above, except that precedence constraints need to be incorporated when t_{now} is initialized. More explicitly, after t_{now} is reset by the first job in the 2nd stage, it is updated to the maximum of the current t_{now} and the maximum completion time of precedent jobs in the 1st stage. For example, the first job in the 2nd stage is destination 10 whose predecessor is vessel 4 in the 1st stage, which requires 2 hours to compete; hence t_{now} = max(0,2) = 2. It is important to notice that more than one chromosome sequence may result in the same objective function value, although each would be decoded into a distinct sequence of jobs.

2.5.2. Initial Solutions

The initialization of GA requires answers for two questions. *First*, how many starting solutions should we have? For this study, we applied TMSTW to model the problem at the Port of Montreal, and then solved it using the proposed GA. Thirty independent runs, ten for each of three different population sizes (80, 100 and 120), were conducted. We noticed that a population with 100 starting solutions yields the best results with lowest computation time, and hence is preferred over population sizes of 80 and 120. *Second*, how are these solutions generated? Although most GAs generates initial population randomly, there is some argument for using a heuristic for the same (Chen et al., 1995; Etiler et al., 2004). We experimented with two cases: the first instance contains only random starting solutions; and the second instance includes a single heuristic solution that sorted jobs in the 1st stage in increasing order of size, and precedent job completion time in the 2nd stage. Table 2-3 is a higher level snapshot of the computational results of the problem instance generated using the parameters for the port of Montreal, which is discussed in detail in Section 2.6.2.

It was noticed that although using heuristic for seeding the algorithm resulted in good initial chromosomes, however each resulted in premature convergence. On the contrary, random initialization makes it possible to generate the critical features of the final solution by search and recombination mechanism of the algorithm. Hence we performed the remaining experiments with completely random starting solutions.

Table 2-3: GA with two different initialization techniques

#Run	OFV(minutes)	
	Random	**Heuristic**
1	44170	45842
2	44995	45739
3	45083	46297
4	44987	47472
5	45832	46272
6	44987	45271
7	44296	45418
8	44910	46332
9	44296	45134
10	45052	46500
Avg	44861	46028

2.5.3. Selection and Crossover

A *binary-tournament* selection method is implemented to choose the parents for generating offsprings, where two parents are randomly chosen and the one with the lower objective function value is selected as a parent. This method allows each member in the population the same chance of being chosen as a parent. The selected chromosomes are subjected to a *two-point* crossover operator to generate offsprings (children). In this scheme, two random points are generated and everything outside the points is swapped between the parents. Two-point crossover is less likely to disrupt schemas with large defining lengths (Mitchell, 1997), which is an important consideration for our problem given the chromosome structure.

Figure 2-5 depicts an example, in which two crossover points, # and *, are employed. Child 1 is generated by preserving the jobs between the two crossover points in Parent 1, and populating the remaining chromosome bit positions with the sequence in which jobs are contained in Parent 2. More specifically: jobs *1*, *5* and *9* are preserved; jobs *2*, *4* and *7* are copied into the three bit positions to the left of the **#** crossover point; job 3 is the next one for assignment, and occupies the first slot to the right of the ***** crossover point, followed by job *8* and then finally by job *6*. Child 2 can be generated similarly.

2.5.4. Mutation

A mutation operator is used to maintain variation between individuals from one generation to the next, and we have used swap mutation where bit values of two randomly selected chromosomes are swapped. We believe that this operator is suitable for our problem since it will not introduce any duplicate values in the chromosome sequence, and hence the resulting chromosome is always feasible. For example, the bit values of the third and eight slots are swapped in Figure 2-6, giving two distinct solutions, both of which are feasible. Please note that we do not consider the jobs' precedence in the mutation process. However it is guaranteed by the decoding procedure: when sequencing the jobs in the second stage, the decoding procedure checks to make sure that all the precedent jobs have been done in the first stage.

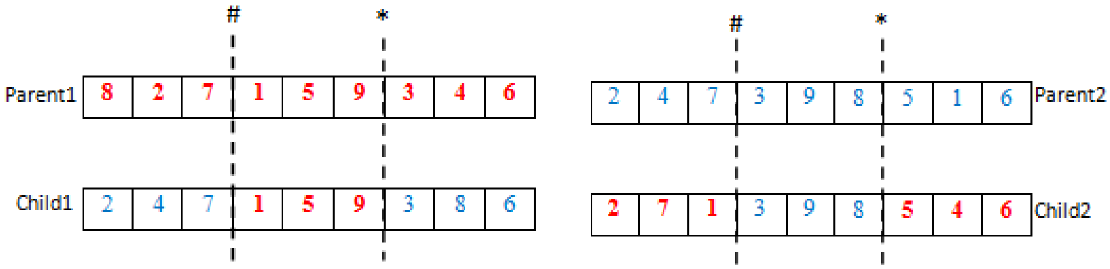


Figure 2-5: Illustration of a two-point crossover

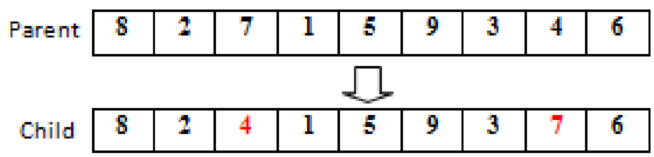


Figure 2-6: Swap mutation

Furthermore, not every chromosome in the pool is selected for crossover and mutation. For our problem instances, a probability of 0.95 was implemented for crossover, and 0.2 for mutation. This implies that the probability of a selected chromosome surviving to the next generation unchanged (apart from any changes caused by the other operator) is 0.05 for crossover and 0.80 for the mutation.

2.5.5. Elitism

To preserve the best solutions encountered during the computational runs, we implemented the elitism scheme proposed by De Jong (1975). We chose to preserve the top 2% of the solutions, i.e., two individual chromosomes with the best fitness values were preserved and moved to the next generation. The proposed GA stops if 1000 consecutive iterations do not produce better solutions.

2.6. Computational Experiments

TMSTW and the GA-based solution methodology were used to solve a number of problem instances of varying size and attributes. In addition, in an effort to demonstrate the effectiveness of the proposed meta-heuristic solution, we also provide results using another meta-heuristic technique: Elitist Evolutionary Strategy (EES). For expositional reasons, we do not discuss EES here and invite the reader to refer to **Appendix A** for relevant details. The results and analysis are organized into four subsections: small size random problem instances; port of Montreal, containing the characteristics of a medium size problem; port of Singapore, one of the largest ports in the world; and large scale random problem instances.

2.6.1. Small Size Random Problem Instances

The nine random problem instances (Table 2-4) were solved using CPLEX and the two meta-heuristic solution techniques. The results are depicted in Table 2-5. The solution methodologies were coded in C# and all numerical experiments were performed on an Intel Core 2 Duo 2.50GHz computer with 4 GB ram. Note that for all these problem instances, the processing time varied between 1 and 8 hours, and the number of cranes varied between 1 and one-third of the number of jobs in a particular stage (i.e., $[1, \frac{n_i}{3}]$). Furthermore, the objective function value (OFV) is in minutes, solution time (ST) is in seconds and refers to the CPLEX CPU time, best-solution time (BT) is in seconds and refers to the time that the meta-heuristic takes to reach the final best solution for the first time.

Table 2-4: Random problem instances

Problem instances	1st stage		2nd stage	
	Vessels	Cranes	Destinations	Cranes
1	3	4	3	5
2			4	6
3			5	7
4			6	8
5	6	9	3	5
6			4	6
7			5	7
8			6	8
9	3	5	16	10

Table 2-5: Comparing the two meta-heuristic techniques

#	CPLEX		GA		EES	
	OFV	ST	OFV	BT	OFV	BT
1	59	0.09	59	0.10	59	0.04
2	75	1.92	75	0.11	77	0.05
3	84	0.64	84	0.35	84	0.18
4	94	1.23	94	0.36	94	0.16
5	109	37.6	109	0.57	109	0.10
6	115	78.8	115	0.60	115	0.18
7	120	133.9	120	0.40	122	0.20
8	137	128.2	137	0.64	137	1.55
9	261	5580	245	65.70	245	54.20

It is clear from Table 2-5 that, for problems 1 to 8 (i.e., small problem instances), both of the techniques can find the optimum solution rather quickly –and in some instances quicker than CPLEX 12.1. Problem set #9 was generated to both highlight the limited effectiveness of the standard optimization package, and also to motivate the relevance of developing solution methodologies for solving even larger problems. For instance, CPLEX could solve #9 to only within 9% of the optimal solution even when allowed to run for over an hour –whereas each of the two meta-heuristics found better solutions in much shorter computational time. Note that although EES is faster than GA, it does not guarantee optimum solution in all instances. For example, problem sets 2 and 7 could not be solved to optimality using EES, because the algorithm was trapped in a local minimum. In the next three subsections, we make use of the two solution techniques to solve larger problem instances.

2.6.2. Port of Montreal

The Port of Montreal, one of the major container ports on the eastern seaboard of North America, is connected to the Atlantic Ocean through the St. Lawrence River and has a well-developed railways and intermodal connectedness. CPLEX and the two meta-heuristic techniques, i.e., GA and EES, were used to solve a problem instance generated using the following parameters for this port.

According to publicly available information (PoM, 2013), the port has eleven berths (i.e.,$n_1 = 11$); fifteen dockside gantry (quay) cranes (i.e.,$m_1 = 15$); and, twenty-six yard (mobile) cranes (i.e.,$m_2 = 26$). Other parameters for TMSTW are estimated as follows: the number of jobs in the 2nd stage, is randomly selected and is set to 19; the number of quay cranes needed in the 1st stage is a random integer selected from $[1, 6]$; the number of yard cranes needed in the 2nd stage is a random integer selected from $[0.1m_2, 0.5m_2]$; the processing time (in minutes) for each job in the 1st stage is randomly selected from the interval $[400, 500]$; and, the processing time for jobs in the 2nd stage is $\frac{0.6P_{1j}Y_{1j}}{Y_{2j}}$, where 0.6 is the ratio of the handling capacity of a quay crane to that of a yard crane (i.e., 25 lifts per hour to 40 lifts per hour). Finally, the weights are assumed to be the same for all jobs, and the availability time windows are selected randomly so that each quay crane has an eight hour rest period between two shifts, and four hours for yard cranes.

A problem instance using the above set of parameters has been generated and solved using CPLEX and the two techniques. CPLEX was run until the optimality was proven, or an out of memory error condition was encountered. Using the best-bound search, CPLEX ran for slightly more than two hours before the search tree exhausted our imposed memory limit of 128 megabytes. The results for the CPLEX and the two meta-heuristics are shown in Table 2-6, where execution time (ET) is in seconds and refers to the total time the meta-heuristic takes before termination. The percentage gap (GAP (%)) is computed as (best OFV – Best Bound) / (best OFV). In minimization problems, such as ours, the Best Bound represents a lower bound on the objective function value of an optimal solution.

According to Table 2-6, the meta-heuristics beat CPLEX in terms of both GAP and computation time. Based on the results, CPLEX found a non-optimal objective function value of 47,344 after exploring 892,957 nodes and performing 8,705,130 (dual simplex) iterations, which is worse than the best solution obtained by both meta-heuristics. The best solutions achieved by GA and EES improve the CPLEX GAP for 2% and 0.6% respectively. In addition, our approaches improved upon the solution provided by CPLEX in significantly shorter time. The average ETs for GA and EES are only 2% and 0.1% of the CPLEX time.

Comparing the two meta-heuristics, it is clear that, EES does not guarantee a superior solution although it reaches the best possible solution much quicker than the proposed GA. On the other hand, the proposed GA beat the EES solution in nine of the ten runs. The proposed GA returned the best encountered solution with an OFV of 44170 minutes, within comparable computing time, and we decode it next.

Table 2-6: Snapshot of ten runs for Port of Montreal

Instances	**GA**			**EES**			**CPLEX**			
	OFV	**ET**	**GAP**	**OFV**	**ET**	**GAP**	**Best Bound**	**GAP**	**OFV**	**ST**
Average	44861			45732						
Best	44170	149.2	31.8	45070	14.5	33.2	30098	33.8	48410	7,430
Std. Dev.	494			394						

Table 2-7 depicts the job sequence and the associated completion time (CT) in minutes for the best solution using the proposed GA. Jobs 1 to 11 belong to the 1st stage while jobs 12 to 30 belong to the 2nd stage. Since a chromosome represents a feasible sequence of jobs for our problem instance, job 11 precedes job 9, and hence the available cranes would be assigned to the former and only then go to the latter. The decoding procedure explained earlier, is used to determine the completion time for each job in the sequence. For instance, the completion time for job 11 is 444, which implies that the total waiting and unloading time for vessel 11 is equal to 7 hours and 24 minutes. Note that the 1st stage is completed after 1408 minutes when job 3, with the maximum completion time, is done. Similarly, the second stage finishes as soon as job 18 is serviced (i.e., 3354 minutes). Since all the jobs have equal priority, the sum of completion time for all the 30 jobs in the given chromosome (i.e., Table 2-7) is the OFV, 44170 minutes.

Table 2-7: Decoded best solution with proposed GA

Jobs	CT	Jobs	CT	Jobs	CT
1	910	*11*	444	*21*	930
2	406	*12*	3062	*22*	808
3	1408	*13*	3064	*23*	730
4	846	*14*	3064	*24*	2381
5	1358	*15*	731	*25*	2381
6	409	*16*	731	*26*	602
7	405	*17*	2874	*27*	2033
8	924	*18*	3354	*28*	1679
9	413	*19*	1198	*29*	1668
10	1287	*20*	2392	*30*	1678

2.6.3. Port of Singapore

In an effort to test the effectiveness of the proposed analytical framework, we consider the characteristics of the port of Singapore, one of the busiest ports in the world with the container traffic of over 29mn in 2011 (CIY, 2012). Seven problem instances based on realistic parameters have been generated, and they are presented in Table 2-8. The remaining parameters such as processing time, number of cranes, and their availability time windows are derived using the technique for the port of Montreal in Section 2.6.2.

Each of the seven problem instances has been run once by CPLEX and 10 times using the two meta-heuristics (Table 2-9). According to Table 2-9, except Problems 1 and 3, CPLEX terminated with a memory fault and no solution. Comparing the results of CPLEX and the best solutions achieved by the two meta-heuristics for the two aforementioned problems proves the superiority of the meta-heuristics in terms of both

GAP and time. For example, for Problem 1, the GAPs reported by GA and EES are approximately 7.5% better than CPLEX, and the solution was obtained in considerably lower time. For the rest of the problems, CPLEX was unable to find a feasible integer solution; hence, the GAP is infinite. However, our developed approaches found relatively good solutions, with GAPs between 26% and 49%.

Table 2-8: Problem parameters for Port of Singapore

Problem Instances	1st stage		2nd stage	
	Jobs	**Cranes**	**Jobs**	**Cranes**
1	6	22	13	59
2	7	25	15	72
3	8	27	17	85
4	9	29	17	107
5	10	31	25	109
6	12	33	24	112
7	14	36	26	114

We also compared the two meta-heuristics. It is clear that the proposed GA-based solution method returns the best solution in six problems, while is tied for the best in another. Once again, it is clear that EES is faster than GA, but it is less likely to return the best solution since it has a tendency to be trapped in local optimums.

Table 2-9: Problem instances for the Port of Singapore solved by CPLEX, GA and EES

#	**CPLEX**				**GA**				**EES**			
	Best Bound¤	**OFV**	**GAP**	**ST**	**Avg.***	**Best**§	**GAP**	**ET**	**Avg.**	**Best**	**GAP**	**ET**
1	18,310	29,791	38.54	4,667	26,901.8	26,702	31	117.8	27,740.6	26,702	31	15.3
2	18,888	-	∞	6,699	27,124.4	26,977	30	142.6	28,622.9	27,356	31	30.1
3	18,043	28,919	37.61	17,505	24,394.8	24,300	26	185.2	24,649.1	24,385	26	26.0
4	19,064	-	∞	15,614	26,891.4	26,734	29	199.8	28,474.4	26,938	29	51.3
5	23,216	-	∞	24,764	37,131.7	35,849	35	292.5	38,584.4	35,889	35	32.8
6	28,028	-	∞	55,430	48,037.6	47,367	41	303.3	51,342.6	47,669	41	39.6
7	32,429	-	∞	112,255	63,404.6	61,534	47	436.0	67,854.6	64,826	49	47.2

¤Best OFV among all the remaining node subproblems; *Average OFV; §Best OFV;

2.6.4. Large Scale Random Problem Instances

To reach more accurate conclusions, a set of large scale instances, has been randomly generated (Table 2-10). Because of the complexity, the generated problems could not be solved by CPLEX in a reasonable time. Thus, only the results obtained by GA and EES are compared here (Table 2-11).

Table 2-10: Random large scale problem instances

Problem Instances	**1st stage**		**2nd stage**	
	Jobs	**Cranes**	**Jobs**	**Cranes**
1	30	90	51	270
2	40	120	87	360
3	50	150	101	450
4	60	180	117	540
5	70	210	141	630
6	80	240	161	720
7	90	270	185	810
8	100	300	205	900

Table 2-11: OFV (minutes) for the large problem instances

#	**GA**				**EES**			
	Avg.	**Best**	**S.D.**	**ET**	**Avg.**	**Best**	**S.D.**	**ET**
1	196,986	196,179	1,141	1,142	269,060	231,141	53,625	848
2	447,011	444,775	3,162	2,392	616,414	600,030	23,170	2,108
3	583,589	575,518	11,413	3,458	962,379	859,509	145,480	2,099
4	850,665	828,790	30,935	4,735	1,240,296	1,220,882	27,456	4,204
5	1,209,115	1,203,520	7,912	7,069	1,874,642	1,789,766	120,032	6,456
6	1,685,925	1,559,875	178,261	7,440	3,012,273	2,423,186	64,401	8,079
7	2,172,178	2,056,653	163,376	10,558	3,012,273	2,933,780	111,005	5,219
8	2,727,264	2,721,673	7,906	11,166	4,213,178	3,950,470	371,525	12,122
9	3,067,782	3,048,280	27,580	13,499	5,005,429	4,969,501	50,809	14,431
10	3,942,918	3,883,914	83,444	14,590	5,898,315	5,779,429	168,129	14,874

Each of the ten random problem instances was solved for ten times using the two meta-heuristics. Please note that the stopping criterion to solve this set of problems is either 1000 consecutive iterations with no better solution or reaching a maximum number of iterations of 100,000. Figure 2-7 presents the relative performance of the two meta-heuristics in terms of ET. It can be observed that GA outperforms EES for all problem instances. It is observed in Figure 2-7 that GA requires more computation time for six problems out of 10.

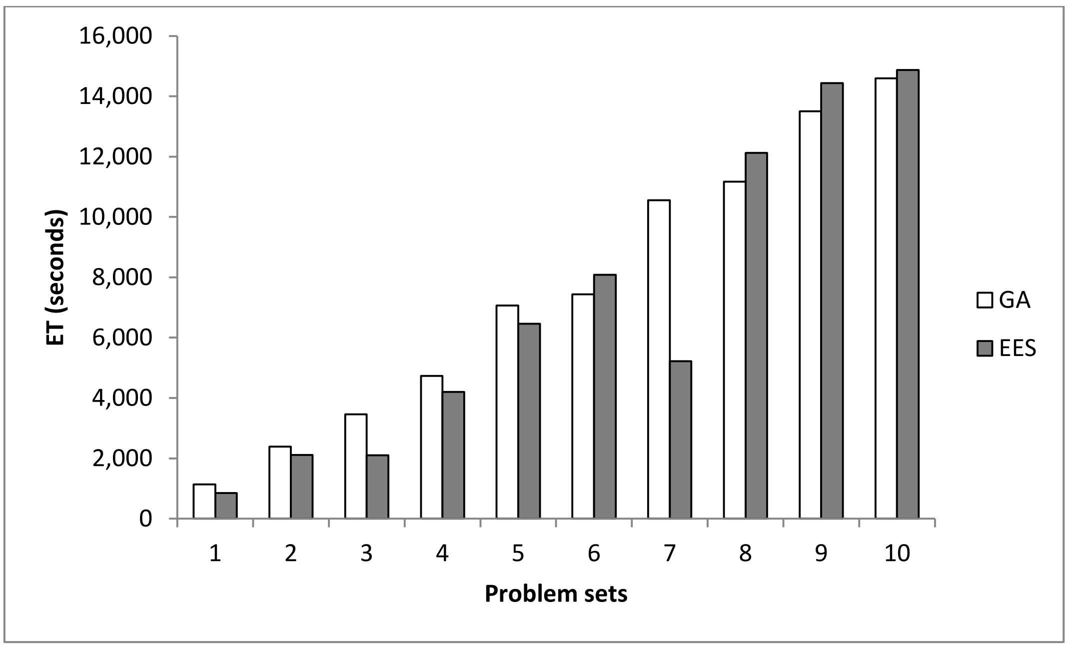


Figure 2-7: ET for GA and EES with the large size problem instances

2.6.5. Managerial Insights

In this section, we ascertain solution sensitivity to perturbation in cranes' time windows, number of cranes, and weights of jobs for the port of Montreal as the base case.

2.6.5.1. Time Windows

To decrease the turnaround times of container ships, trucks and intermodal trains, either the availability time windows or the number of the cranes could be increased. To determine the impact of variations in the availability time windows of cranes on the total weighted completion time (OFV), the current unavailability time spans were halved and doubled. When the unavailability times are doubled, the jobs have to be completed in longer time, with an OFV of 47702 minutes. However, when the unavailability times are halved, the OFV decreases to 43707 minutes (Figure 2-8).

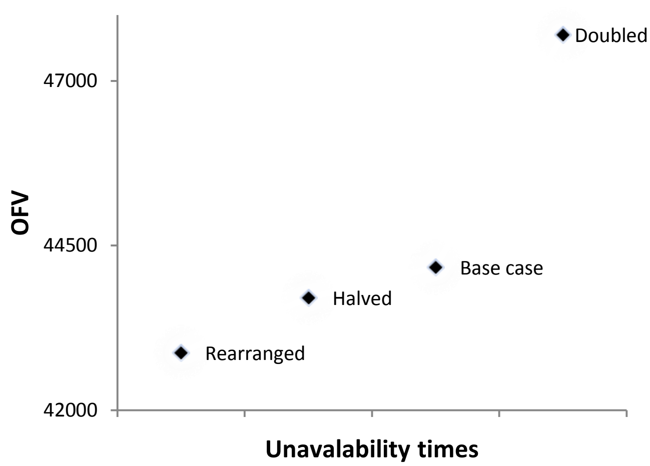


Figure 2-8: Impact of unavailability time windows on OFV

It was interesting to note that in addition to the duration, the distribution of unavailability times had a direct bearing on the completion time. This implied that the unavailability time windows could be arranged so as to ensure smooth flow of jobs –without changing the actual unavailability duration. This was done by moving the unavailability times for the quay cranes in the first stage to the end of their schedule, which ensured that the waiting times of the jobs was minimized. On the other hand, the unavailability times for the yard cranes in the second stage were moved to the beginning of the schedule, which in turn guaranteed their availability to serve jobs released from the first stage. TMSTW was solved using the rearranged unavailability time windows, and the total completion time decreased to 42877 –which is the lowest of all the computed instances (Figure 2-8). Hence, port management interested in quick turnaround of containers should consider the processing time of jobs and the related interdependencies when designing unavailability time windows for the cranes. For example, if, in a container port terminal, the total amount of unavailability should not exceed 15 percent of the total available time, one could search for the optimal occurrence of the unavailability time spans, so that the waiting times of the jobs are minimized.

2.6.5.2. Number of Cranes

We also investigated the impact of variations in number of cranes on the solution. When we increase the number of quay and yard cranes to 29 and 44 respectively, the OFV decreases to 35073 minutes, however, the decrease of the number of quay and yard cranes respectively to 11 and 19, worsen the OFV to 54460 minutes (Figure 2-9). Based on the results, acquiring additional resources (cranes in this study) can considerably reduce the turnaround time, by decreasing the waiting times. It is important to note that, the results may be different when we take the interferences among cranes into account. According to Bierwith and Meisel (2009), interferences among cranes alter their overall performance.

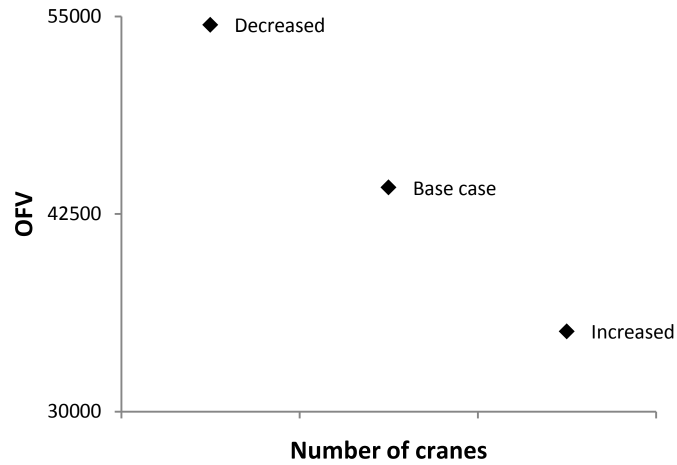


Figure 2-9: Impact of number of cranes on OFV

2.6.5.3. Job Weights

In an effort to ascertain the impact of variations in weights on the solution, we assigned higher priority to three jobs: *3* in the 1st stage; and, *17* and *18* in the 2nd stage, assuming they are related to the similar type of hazmat containers, e.g. containers of propane. After solving the model, we notice that these jobs were completed much earlier (Table 2-12) than when all jobs had equal weight (Table 2-7), although the total completion time increased to 44 856 minutes. This implies that in general attaching higher priority would ensure earlier completion of the given task provided that there are available resources, although that may not necessarily result in better overall completion time, and indeed might make it worse.

In the next experiment, we assumed that there are two types of hazmat containers, i.e. in addition to the jobs related to the containers of propane (job *3* in the 1st stage; and jobs *17* and *18* in the 2nd stage) with priority of 2, we considered jobs associated with radioactive containers (job *11* in the 1st stage; and jobs *28*, *29* and 30 in the 2nd stage) with higher priority of 3. The total completion time increased to 45645 minutes; however, the completion time of jobs *11*, *28*, *29* and *30* considerably decreased to 444, 1392, 1392 and 1392.

Table 2-12: Impact of weights

Jobs	**CT**	**Jobs**	**CT**	**Jobs**	**CT**
1	924	*11*	1291	*21*	3313
2	888	*12*	669	*22*	3313
3	406	*13*	1200	*23*	994
4	405	*14*	2628	*24*	2712
5	847	*15*	1449	*25*	772
6	1426	*16*	1882	*26*	1882
7	1336	*17*	1097	*27*	2279
8	413	*18*	3313	*28*	1908
9	448	*19*	776	*29*	776
10	409	*20*	2388	*30*	2712

2.7. Conclusion

High operating costs of container ships imply that any delay at the ports could result in huge loss to the ship operators, as well as the final customers in terms of delayed deliveries and higher price. This study proposed an analytical approach that can be used to schedule the cranes at maritime terminals, such that the unloading of inbound vessels and the loading of outbound vehicles could be completed in minimum time. The methodology calls for a multi-processor multi-stage scheduling approach to the managerial problem, where each processor has an availability time window. Hence, this work contributes to the area of scheduling available resources at a cross docking facility.

Since the proposed model is NP-hard, only small size problem instances can be solved using the exact methods. Hence, we have outlined a solution method based on a genetic algorithm (GA) equipped with a novel decoding procedure. This method has been tested on problem sets generated using realistic parameters from the Port of Montreal and the Port of Singapore, as well as a set of large scale problems. In order to demonstrate the efficiency of the proposed technique, we compared its performance to CPLEX and another meta-heuristic technique (Evolutionary Strategy). The computational results showed that the proposed GA quickly finds known optimal solutions for small size problems. For the larger instances for which optimal solutions are not known, GA improved upon the best solutions provided by CPLEX but in a fraction of the time. It also outperforms EES in most instances, and within a reasonable amount of computing time.

The limitation of this study is that a job in the second stage is forced to wait for the entire vessel to be unloaded before it can proceed with its operation. In the future research, we will redefine the job in the first stage as a smaller size construct, with consideration of the corresponding successor in the second stage. Additionally, it would be interesting to investigate the effect of increasing the number of cranes assigned to the jobs and the level of interference between the cranes on the completion time. Furthermore, the situation in which each vessel has dynamic arrival time will be investigated in the future to evaluate the efficiency of the port in terms of average waiting turnaround times.

This chapter aims to schedule the cranes available in intermodal terminals, while the capacity planning of those terminals, i.e. how many cranes each terminal should choose, is the subject of the next Chapter. In other words, unlike this chapter where the number of cranes available in the terminal was regarded as a parameter of the model, in the next chapter it will be considered as a decision variable. Chapter 3 studies a tactical level problem of routing and capacity planning in an intermodal network.

2.8. Appendix A

2.8.1. Elitist Evolutionary Strategy

An alternative to GAs are evolutionary strategies that were founded by Rechenberg (1973) to solve real valued problems, in which chromosomes are represented as arrays of real valued numbers instead of bit strings. These algorithms are mainly used for empirical experiments. In comparison to GA, mutation plays a more important role to evolve the individuals in evolutionary strategies.

In this research we use the elitist evolutionary strategy which enjoys elitism and ranking selection. Elitism makes it possible for the parents to survive an infinitely long time-span and guarantees the global convergence of evolutionary strategy (Beyer and Schewefel, 2002). The two main parameters of this algorithm are (1) μ, the number of parents used to produce children, and (2) λ, the number of children produced in each iteration. After creating μ solutions as the initial population, λ offsprings are generated by mutation. Combining and sorting the μ parents and λ offsprings, the μ fittest individuals are chosen and preserved for the next generation. Evolutionary strategies are fast and can readily find local optima, yet they may not be able to achieve the global optimum. The pseudo code of elitist evolutionary strategy is presented in Figure 2-10.

Other considerations for the implemented evolutionary strategies are as follows.

- μ: 1
- λ: 10
- Probability of mutation: 0.2

```
Create the parentPop of μ solutions
while not Termination Condition() do
    for individual: 1 to μ do
        for count: 1 to λ/μ do
            offspring =Mutation (individual);
            offspringPop.add (offspring);
        end for
    end for
    for individual: 1 to μ do
        offspringPop.add (individual);
    end for
    Sort offspringPop;
    Clear parentPop;
    for count: 1 to μ do
        parentPop.add (offspring);
    end for
end while
```

Figure 2-10: Elitist evolutionary strategy

3. Managing Rail-truck Intermodal Transportation for Hazardous Materials with Congestion Considerations

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.

Keywords: Rail-truck Intermodal; Congestion Effect; Hazardous Material; Capacity Planning; Nonlinear Integer Program

3.1. Introduction

Hazardous material (hazmat) is a substance or material that is capable of posing an unreasonable risk to health, safety, and property when transported in commerce (U.S. Environmental Protection Agency, 2013). Examples of hazmat include gases, flammables, explosives, and radioactive materials (Verter, 2011). Although hazardous materials are source of potential of harm, they cannot be eliminated from our lives, as they are essential to our economies and our technology dependent societies. Large volumes of hazardous materials are transported every day. According to the Office of Hazardous Materials Safety (OHMS) of the US DOT, 800,000 hazardous material shipments were carried out daily in United States in 1998 (US DOT, 2010). With a conservative estimate, production and shipment of hazardous material tend to increase by 2% annually, and the total number of shipments every year in America has been over one million since 2005 (Erkut et al., 2007). With 99.97% of the 1.7 million carloads of hazardous materials successfully reaching their final destination without incident (AAR, 2012), rail is by far claimed to be the safest way to move hazardous materials. However, recent train disasters, such as Lac-Mégantic, Alabama and Louisiana derailments, show that rail transportation is not as safe as it was, especially when it comes to shipment of high concentrations of hazardous materials via tracks passing through populated areas. Hence, active measures should be taken by relevant stakeholders to mitigate the risks caused by hazmat transportation.

Intermodal transportation refers to transporting a shipment from a shipper to a receiver through multiple transportation modes (Crainic and Kim, 2007). Among all the hazmat shipments reported in the US, 111 million tons of hazmat were carried through multiple modes, which accounts for around 13.3% of all modes of hazmat transportation by ton-miles (US DOT, 2010). In the past few decades, intermodal transportation, especially rail-truck intermodal transportation (RTIM), has grown exponentially. Due to its advantages in reducing the uncertainties and lead times (Nozick and Morlok, 1997), RTIM has been employed to ship both regular freight and hazmat.

Figure 3-1 depicts a typical rail-train intermodal transportation chain. As shown, transporting a container from the shipper to receiver must pass through three portions: 1) inbound drayage by trucks from the shipper to the origin terminal, 2) rail-haul from the origin intermodal terminal to the destination terminal, and 3) outbound drayage by trucks from the destination terminal to the receiver. The double connections from one member to the other indicate that alternative routes are available in each portion of this chain. More particularly, although the number of rail routes between the origin and destination terminals is limited, multiple train services can be maintained in terms of speed, departure time, intermediate stops, and routes (Verma and Verter, 2010). Please also note that the rail-haul service for shipping hazmat usually operates on a fixed-schedule, non-stop from the origin to the destination terminal.

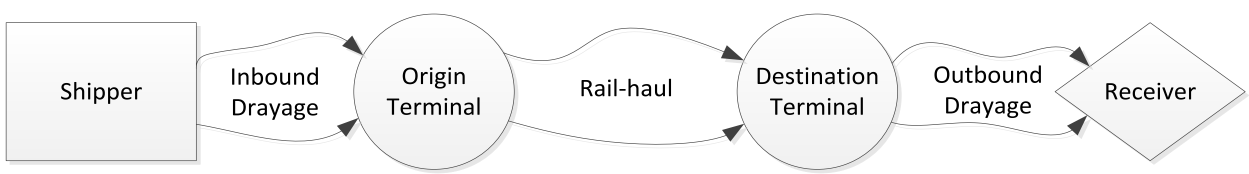


Figure 3-1: A rail-truck intermodal transportation chain

As shown in Figure 3-1, intermodal terminals are the key components of any intermodal transportation network. Unloading containers from trucks and loading them into trains are provided by special equipment at origin terminals, while unloading of containers from trains and loading of them into trucks are done in destination terminals. When transported to the terminal by truck/ train, the containers are either directly transferred to a rail car/truck or are stacked temporarily in a waiting area. As discussed in the literature review (Section 3.2), most existing research ignored the operations within an intermodal terminal from hazmat perspective. When the demand is uncertain, this ignorance may result in many serious issues related to intermodal transportation, especially the hazmat transportation, such as the underestimation of delivery time and the possible exposure risk caused by congested hazmat shipments.

In dealing with these issues, we propose a bi-objective nonlinear programming model for managing rail-truck intermodal transportation of hazardous materials. The issue of cost is always the main concern of every decision making process, and thus is addressed as our first objective. This research considers three costs: 1) the transportation cost of the three portions of the intermodal transportation chain; 2) the fixed cost of opening and maintaining a certain train service; and 3) the purchase cost of handling equipment at each terminal. Among the aforementioned costs, the drayage cost is a function of time the crew is engaged and the estimated consumed fuel, while the rail-haul cost depends on the type of the service, in our case, either regular or priority. In addition to the rail-haul cost and regardless of the number of cars assigned to a train, there is a fixed cost for operating a train service that mainly consists of the wages of the train crews. Inside each intermodal terminal, the equipment used for moving containers from trucks to trains (or trains to trucks) can be expensive. Also the number of these equipment items has direct effect on the level of congestion at an intermodal terminal. Therefore, it is necessary for the decision maker to ensure the right number of equipment items that should be purchased, such that the congestion of the transportation flow is limited, but with the lowest cost.

Because of the associated environmental risks, planning and decision-making in the context of hazmat shipments is different from the regular ones. Here we formulate the total risk as the second objective. As one of the most applied risk measures, population exposure refers to the total number of people exposed to the undesirable consequence due to the movement and opening of hazardous facilities (such as gas stations and hazardous waste treatment centers). In our research, besides the population exposure caused by the inbound and outbound drayage, as well as the rail-haul, we further investigate the possible risk resulting from the hazmat containers staying (waiting for service) in the intermodal terminals. The larger the number of hazmat containers staying in the system, the higher the exposure risk to surrounding population. To model the exposure risk due to congestion of hazmat containers, we consider each piece of equipment as a server of a non-preemptive priority queuing system, where hazmat containers have non-preemptive priority over regular containers. Details about the evaluation of this risk will be discussed in Section 3.3.

To the best of our knowledge, this is the first study that considers congestion of hazmat freights as a source of exposure. Our suggested model would help decision makers identify the risky terminals and adopt appropriate policies for risk management. The remainder of this chapter is organized as follows. Section 3.2 provides a thorough review of the relevant literature. Section 3.3 shows the problem statement and discusses model assumptions. A bi-objective nonlinear programming model is developed and investigated in Section 3.4. Section 3.5 discusses the solution procedure, while Section 3.6 presents a numerical experiment conducted with real-world data. Through our computational experiments a number of problem instances will be solved and analyzed to determine the factors affecting congestion risk and gain managerial insights. Section 3.7 concludes this Chapter with managerial insights and contributions.

3.2. Literature Review

In the following, we conduct a comprehensive literature review regarding: 1) risk modeling in location routing problems, 2) intermodal transportation for hazardous materials, 3) consideration of congestion effects and 4) terminal operations.

The first group of papers models the risk in location routing problems. A lot of effort has been made to capture the transportation risk using operations research models. Among various risk measurement methods, three prominent models of measuring the path risk are traditional risk, population exposure, and incident probability. Traveling on a P consists of multiple edges which can be viewed as a probabilistic experiment. In other words, a hazmat vehicle will travel the ith edge of P only if there is no accident on the previous ($i - 1$) edges of P. Assuming that the probability of accident on edge i is p_i, the risk associated with travel along path P consists of n edges has the linear form of $\sum_{i=1}^{n} p_i c_i$, where c_i denotes the total population in the rectangle shape impact area that stretches along edge i. Because of using the expected consequence definition of risk, this method is called the traditional risk model, which has been applied by Batta and Chiu (1988), Alp (1995) and Zhang et al. (2000). In addition to the traditional risk, Batta and Chiu (1988) used population exposure to measure the path risk. In this method, the population exposure is approximated by $\sum_{i=1}^{n} c_i$, where c_i denotes the total population in the rectangle shape impact area that stretches along edge i. The third model takes the probability of incident when measuring the risk: $\sum_{i=1}^{n} p_i$. Saccomanno and Chan (1985) and Abkowitz et al. (1992) used the incident probability in their researches.

In the following, we review a number of papers that studied location routing problems with regard to hazmat risks. Revelle et al. (1991) suggested an optimization model to find the location of waste disposal facilities and to choose routes for the shipment of hazardous waste, so that the transportation costs and perceived risks are minimized. They accounted the perceived risk in terms of the number of people who are most likely to suffer risks associated with shipment along the arc from the origin to the destination. List and Mirchandani (1991) captured the transport and facility risk in a waste treatment network. They defined the transportation risk as a function of external impact due to the shipment. They also indicated that the impact to a specific point from a vehicle incident is inversely proportional to the square of the distance between the vehicle and that point, and is directly proportional to the volume being shipped. The facility risk was determined in a same way. Stowers and Palekar (1993) developed a bi-objective model of locating hazardous waste repositories. Aiming to minimize the total and the maximum exposure, this model quantifies the total exposure of the population during the transportation and long term storage. Similar to Revelle et al. (1991), this study assumed that the presence of hazardous waste at any point on the network exposes a circular region of constant diameter to risk. The total exposure to a node or to an arc of the network was defined as a convex combination of location exposure and travel exposure. Giannikos (1998) defined the total perceived risk as the summation of risk perceived by individuals at different centers. A multi-objective model was developed to determine the location of disposal facilities and transportation of hazmat waste, considering four objectives: 1) minimization of total operating cost; 2) minimization of total perceived risk; 3) equitable distribution of risk among population centers to minimize the maximum individual perceived risk; and 4) equitable distribution of the disutility to minimize the maximum individual disutility caused by the operation of the treatment facilities. Cappanera et al. (2004) studied the problem of locating obnoxious facilities (e.g. dump sites) and routing obnoxious materials between communities and facilities. Their model minimizes the opening cost of facilities and the transportation cost of the obnoxious flow, while restricting the location and routing exposures caused by settling facilities near a built-up area (affected site) to a predetermined level. That is, the total transportation and opening exposures must not exceed the thresholds, knowing the exposure by a unitary flow along the arcs and the exposure caused by the opening of a facility at a specific location. A multi-objective model for hazardous waste location routing problem was suggested by Alumur and Kara (2007). The model aims to determine the location of treatment and disposal centers, as well as the routing of different types of hazardous wastes and waste residue to those centers. The first objective minimizes the total cost of transportation and the fixed annual cost of opening a treatment technology and a disposal facility. The second objective minimizes the total risk of transportation, which is measured with population exposure. A similar multi-objective location-routing model was presented by Samanlioglu (2013) who considered the recycling centers besides the treatment and disposal centers. In addition to the minimization of the total cost and the total transportation risk, the developed model minimizes the total risk for the population living near the centers (treatment, disposal and recycling centers).

Despite the efforts having been put into the risk evaluation related to location routing problems for hazmat transportation, only few studies have considered the transportation through intermodal networks. Our next Section reviews existing literature in dealing with intermodal transportation for hazardous materials.

The second class of papers studies the intermodal transportation for hazardous materials. More specifically, we consider rail-truck intermodal transportation network. The rail-truck intermodal transportation is a safe way of shipping hazmat cargoes. It is not simply the combination of two modes of rail and truck, but also includes the division of tasks and the synchronization of schedules (Bontekoning et al., 2004). However, very limited research has been done in the area of rail-truck intermodal transportation for hazmat. Verma and Verter (2010) are the first authors who studied the rail-truck intermodal network for transportation of hazardous materials. They developed a multi-objective model to determine the best shipment plan for hazardous and regular freights, so that a set of predetermined lead times are satisfied, and the total cost and risk are minimized. A nonlinear risk function was defined to calculate the population exposure caused by the operations of trains between each single pair of intermodal terminals. The model was then generalized by Verma et al. (2012) to consider multiple intermodal terminals. Xie et al.

(2012) combined the facility location and routing problems for multimodal transportation of hazardous materials. They considered a network of highways and railways, where hazmat can be transferred between trucks and rail cars only at transfer yards. To optimize transfer yard locations and routing plans, they developed a multi-objective model which minimizes the cost, including total link cost, the transfer yard's capital and operating costs, as well as risks, including the link risk and the risk during the transfer process.

Although the risk exposure has been considered in the strategic and tactical planning of intermodal transportation of hazardous materials, the sources of this exposure have been limited to the moving of hazardous materials and the location of intermodal terminals. Assuming deterministic demand as well as sufficient capacity and equipment, the existing literature overlooked the possibility of congestion at any point in the intermodal chain, not to mention the exposure caused by the congestion of hazmat shipments, especially the congestion at the intermodal terminals.

The third class of papers considers the congestion effects. In traditional optimization problems, demand is assumed to be constant and deterministic over the time, and capacity constraints are usually used to avoid the effects of congestion. In contrast, the probabilistic models define the demand as a stochastic process and use Markovian queuing to deal with the congestion. Some of the recent stochastic models considering the congestion effects are reviewed as follows. As the first work that studied location problems with stochastic demands and congestion, Marianov and Serra (1998) assumed a Poisson arrival of service requests and exponential service time. Multiple maximal covering location allocation problems were developed subject to a predetermined waiting time, i.e. congestion time. Both M/M/1 and M/M/m queuing systems were examined in this paper. Marianov and Serra (2001) further studied the hierarchical version of the location allocation problem in presence of congestion. They considered low and high level service centers that respectively employ the M/M/1 and M/M/m queuing systems. Capacity planning with regard to congestion effects was studied by Rajagopalan and Yu (2001). They considered a multi-product and multi-machine production system, where each product can be produced on a single machine, and each machine was modeled as an M/G/1 queue. The equipment acquisition model was formulated as a nonlinear integer program, which minimizes the total cost while the targeted service level at each machine is met. Congestion effects in airline network were investigated by Marianov and Serra (2003) who modeled the airports as M/D/c queuing systems. They developed a model to determine the location of airports, so that the transportation cost and fixed cost of locating the airports are minimized, while the probability of more than a certain number of airplanes waiting in the queue is kept less than a predetermined value. The purchasing cost was first incorporated in the objective function by Elhedhli and Hu (2005). They studied a hub-and-spoke network design problem, in which the purchasing cost at a hub is defined as a convex function, so that the cost increases exponentially as more flows are routed through that hub. Elhedhli and Wu (2010) embedded congestion in the design of a hub-and-spoke system which was viewed as a network of M/M/1 queues. They suggested a nonlinear mixed integer model to minimize the congestion, capacity acquisition and transportation cost. The congestion at hubs was calculated as the ratio of total flow to surplus capacity.

Most literature discussed in this section examined the congestion effects in the constraints, ensuring that the congestion time or the number of waiting units is lower than a specific level. The last two papers investigated congestion at the objective stage, but only regular freights have been addressed. With consideration of the hazmat transportation, congestion effects become more important yet challenging.

Finally, the fourth group of papers is related to the operations inside the terminal. In a rail-truck intermodal network containers arrive at the terminal by truck/train and are either directly transferred to a rail car/truck or are stacked temporarily in a waiting area. As far as we know, there are only a few papers that study inland terminal operations. Gambardella et al. (2001) studied resource allocation and scheduling of loading and unloading operations in an intermodal container terminal. At the allocation level, their suggested approach aims to determine the best allocation of resources at the yard so that the costs are minimized, while at the scheduling level, the objective is to schedule the unloading and loading operations so that the resource usage is optimized. An optimization model for a rail-rail container terminal was developed by Alicke (2005). Alicke developed a framework based on constraint programming to determine the sequence of transshipments and the size of the crane areas. In another study, an assignment model to dynamically assign containers to slots on intermodal trains was presented by Corry and Kozan (2006). The model aimed to minimize the excess handling time and to optimize the weight distribution of the train. A literature review on container terminal operations was provided by Stahlbock and Voß (2008).

However few papers scrutinize operations in inland terminals, a significant number of papers study similar issues at container port terminals. Quay-crane scheduling, stowage planning and sequencing and storage space planning are the main problems related to container port terminal operations. For comprehensive overviews on the operations in sea terminals, we invite readers to refer to Crainic and Kim (2007).

3.3. Problem Description

This section provides a comprehensive description of the problem focused in our research. Based upon the intermodal chain illustrated in Figure 3-1, our research aims to answer the following three questions so as to minimize the total cost and risk.

1) How many intermodal train services should be maintained?
2) How to route hazmat and regular containers to their destinations through the origin and destination terminals?
3) What should the capacity of each intermodal terminal be? That is, how many equipment items each terminal should choose considering the congestion effects?

The first and second questions are tactical level decisions related to the number of train services and the routing aspect of the model. As Figure 3-1 shows, in a typical rail-truck intermodal transportation network, there are multiple route choices connecting one part to the other, each of which has particular travel time, cost and exposure. There are also multiple train services with different intermediate stops, speeds, routes and departure time. Findings of Verma et al. (2012) for a congestion-free network with deterministic demand show that the use of non-stop train services and selection of longer but less risky paths can minimize the transportation risk of hazmat containers.

The third question is a strategic decision and concerns the the relationship between the capacity of an intermodal terminal and congestion, which is considered as a source of exposure in our model. We assume that decision maker has selected M_j (M_k) pieces of equipment of the same type for possible acquisition at each origin (destination) terminal j (k). Each piece of equipment is considered as a server in a non-preemptive priority queuing system, in which members of the queue are selected for service based on their assigned priorities. More specifically, hazmat containers have non-preemptive priority over regular containers, i.e. the arrived hazmat containers move to the head of the queue, but the regular containers in service are not interrupted. Further information on priority queue disciplines can be found in Gross and Harris (1998).

A Poisson process is a random process used in queuing theory. It is described by its rate parameter, λ, which is the expected number of events or arrivals that occur per unit time. We model arrivals of the requests for transportation of the hazmat and regular containers in a certain time period as independently distributed Poisson processes. By a “request”, we mean the request for transportation of a hazmat or regular container from a shipper to a receiver in a certain time period. It is interchangeable with the term “demand” in this research.

We assume that the requests for handling the hazmat and regular containers arrive independently and both follow Poisson processes in a certain time period, and the service time of the equipment is exponentially distributed. These assumptions are very common in the modeling environments that consider congestion (Rajagopalan and Yu, 2001). Since all the containers transported from shippers enter the origin terminals, the input process to the equipment in these terminals is a Poisson process. It is easy to prove that the input process to the equipment in the destination terminals is also a Poisson process: according to the equivalence property, an infinite queue with a Poisson input described by parameter λ_{mj} and exponential service time μ ($\lambda_{mj} < \mu$) has a Poisson output with parameter λ_{mj}. Since the containers leaving the origin terminals are entirely transported to the equipment in one or more corresponding destination terminals, these equipment items in the destination terminals also have a Poisson input. This property makes no assumption about the type of queue discipline, so it can be applied to priority queues in our case too.

A sample queuing diagram of origin terminal j and destination terminal k with respectively three and two pieces of equipment is presented in Figure 3-2. λ_{mj} and $\bar{\lambda}_{mj}$ (m = 1, 2, 3) are, respectively, the hazmat and regular arrival rates of containers to equipment m in origin terminal j (for terminal k, m = 1, 2). The service rate of equipment at origin terminal j is μ_j and at destination terminal k is μ_k. Given the aforesaid assumptions, we formulate the congestion risk as the average number of hazmat containers waiting in the queue.

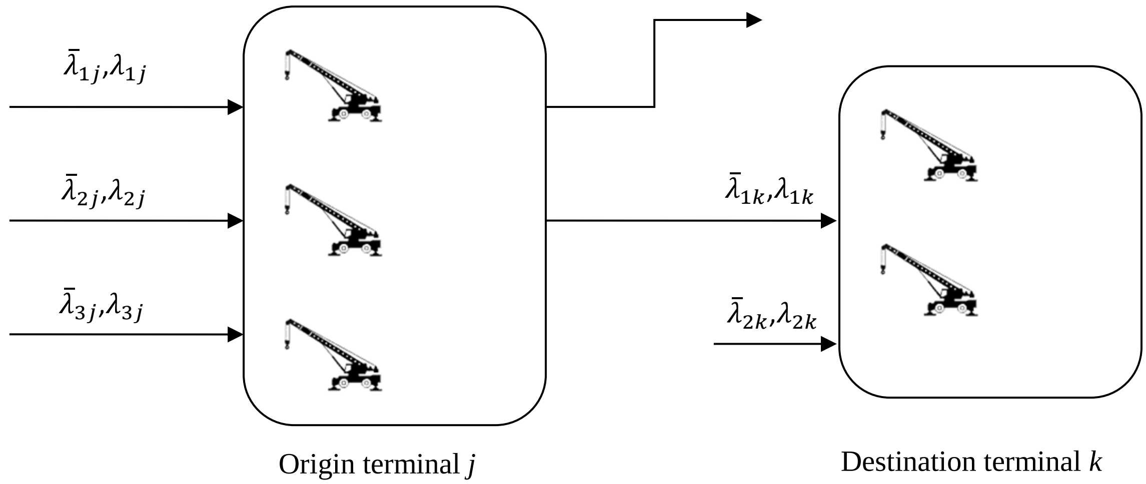


Figure 3-2: A view of queuing at origin terminal j and destination terminal k with respectively three and two pieces of equipment

3.4. A Bi-objective Model

In this section, we present a bi-objective nonlinear programming model (P) for managing rail-truck intermodal transportation of hazardous materials.

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 traffic-classes, indexed by z. The elements of this set are derived from pairing every shipper $i \in I = \{1, 2, \ldots, a\}$ with the receiver $l \in L = \{1, 2, \ldots, f\}$

it supplies.

P_{ij} Set of inbound drayage between each shipper $i \in I = \{1, 2, \ldots, a\}$ and each origin terminal $j \in J = \{1, 2, \ldots, b\}$, indexed by p.

O_{kl} Set of outbound drayage between each destination terminal $k \in K = \{1, 2, \ldots, e\}$ and each receiver $l \in L = \{1, 2, \ldots, f\}$, indexed by q.

V_{jk} Set of intermodal train services between each terminal pair j-k, where $j \in J = \{1, 2, \ldots, b\}$and $k \in K = \{1, 2, \ldots, e\}$, indexed by v.

S_{jk}^{v} Set of train service legs for intermodal train service type v operating between terminals $j \in J = \{1, 2, \ldots, b\}$ and $k \in K = \{1, 2, \ldots, e\}$, 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 destination terminal k, indexed by m'

Input parameters:

O A large number

C^p Cost of moving one hazmat container on path p for inbound drayage

$\bar{C}^p$ Cost of moving one regular container on path p for inbound drayage

C^v Cost of moving one hazmat container using intermodal train service of type v

$\bar{C}^v$ Cost of moving one regular container using intermodal train service of type v

C^q Cost of moving one hazmat container on path q for outbound drayage

$\bar{C}^q$	Cost of moving one regular container on path *q* for outbound drayage
B_j	Purchase cost of an equipment at origin terminal *j*
B_k	Purchase cost of an equipment at origin terminal *k*
FC^v	Fixed cost of operating intermodal train service of type *v*
E^p	Population exposure due to moving one hazmat container on path *p* for inbound drayage.
E^v	Population exposure due to moving one hazmat container on intermodal train service of type *v*.
E^q	Population exposure due to moving one hazmat container on path *q* for outbound drayage.
E^j	The exposure caused by a unit of hazmat container in the queue of an equipment in origin terminal *j*
E^k	The exposure caused by a unit of hazmat request in the queue of an equipment in destination terminal *k*
t^p	Inbound drayage time using path *p*
t^v	Travel time of intermodal train service of type *v*
t^q	Outbound drayage time using path *q*
DT_z	Delivery time associated with traffic-class *z*

U^v	Maximum number of containers that can be loaded on intermodal train service of type *v*
μ_j	Service rate at each equipment at origin terminal *j*
μ_k	Service rate at each equipment at origin terminal *k*
D_z	Expected demand for hazmat containers in traffic-class *z*
$\overline{D}_z$	Expected demand for regular containers in traffic-class *z*

Decision variables:

X_z^p	Expected hazmat containers of traffic-class *z* using path *p* for inbound drayage
$\bar{X}_z^p$	Expected regular containers of traffic-class *z* using path *p* for inbound drayage
X_z^v	Expected hazmat containers of traffic-class *z* on train service of type *v*.
$\bar{X}_z^v$	Expected regular containers of traffic-class *z* on train service of type *v*.
X_z^q	Expected hazmat containers of traffic-class *z* using path *q* for outbound drayage
$\bar{X}_z^q$	Expected regular containers of traffic-class *z* using path *q* for outbound drayage
Y_z^P	1 if $X_z^p > 0$; 0 otherwise
Y_z^v	1 if $X_z^v > 0$; 0 otherwise
Y_z^q	1 if $X_z^q > 0$; 0 otherwise

$\bar{Y}_z^P$ 1 if $\bar{X}_z^p > 0$; 0 otherwise

$\bar{Y}_z^v$ 1 if $\bar{X}_z^v > 0$; 0 otherwise

$\bar{Y}_z^q$ 1 if $\bar{X}_z^q > 0$; 0 otherwise

N^v Number of intermodal train service of type *v*

H_{mj} 1 if new equipment *m* in origin terminal *j* is acquired; 0 otherwise

$H_{\acute{m}k}$ 1 if new equipment *m′* in destination terminal *k* is acquired; 0 otherwise

λ_{mj} Arrival rate of hazmat containers to equipment *m* in origin terminal *j*

$\bar{\lambda}_{mj}$ Arrival rate of regular containers to equipment *m* in origin terminal *j*

λ_{mk} Arrival rate of hazmat containers to equipment $\acute{m}$ in destination terminal *k*

$\bar{\lambda}_{\acute{m}k}$ Arrival rate of regular containers to equipment $\acute{m}$ in destination terminal *k*

$$\min \sum_{z\in Z_{il}} \sum_{p\in P_{ij}} \left[C^p X_z^p + \bar{C}^p \bar{X}_z^p\right] + \sum_{z\in Z_{il}} \sum_{q\in Q_{kl}} \left[C^q X_z^q + \bar{C}^q \bar{X}_z^q\right] +$$

$$\sum_{z\in Z_{il}} \sum_{v\in V_{jk}} [C^v X_z^v + \bar{C}^v \bar{X}_z^v] +$$

$$\sum_{v\in V_{jk}} FC^v N^v + \sum_{j\in J} \sum_{m\in M_j} B_j H_{mj} + \sum_{k\in k} \sum_{\acute{m}\in M_k} B_k H_{\acute{m}k} \tag{3-1}$$

$$\min \sum_{z\in Z_{il}} \sum_{p\in P_{ij}} E^p X_z^p + \sum_{z\in Z_{il}} \sum_{q\in Q_{kl}} E^q X_z^q +$$

$$\sum_{z\in Z_{il}} \sum_{v\in V_{jk}} E^v X_z^v + \sum_{j\in J} \sum_{m\in M_j} E^j \lambda_{mj} \frac{\lambda_{mj}+\bar{\lambda}_{mj}}{\mu_j(\mu_j-\lambda_{mj})} + \sum_{k\in K} \sum_{\acute{m}\in M_k} E^k \lambda_{\acute{m}k} \frac{\lambda_{\acute{m}k}+\bar{\lambda}_{\acute{m}k}}{\mu_k(\mu_k-\lambda_{\acute{m}k})} \tag{3-2}$$

s.t.

$$\sum_{p\in P_{ij}} X_z^p = \sum_{v\in V_{jk}} X_z^v, j \in J, z \in Z_{il} \qquad \text{(a)} \qquad \text{(3-3)}$$

$$\sum_{p\in P_{ij}} \bar{X}_z^p = \sum_{v\in V_{jk}} \bar{X}_z^v, j \in J, z \in Z_{il} \qquad \text{(b)}$$

$$\sum_{v\in V_{jk}} X_z^v = \sum_{q\in Q_{kl}} X_z^q, k \in K, z \in Z_{il} \qquad \text{(c)}$$

$$\sum_{v\in V_{jk}} \bar{X}_z^v = \sum_{q\in Q_{kl}} \bar{X}_z^q, k \in K, z \in Z_{il} \qquad \text{(d)}$$

$$\sum_{q\in Q_{kl}} X_z^q = D_z, z \in Z_{il} \qquad \text{(a)} \qquad \text{(3-4)}$$

$$\sum_{q\in Q_{kl}} \bar{X}_z^q = \bar{D}_z, z \in Z_{il} \qquad \text{(b)}$$

$$\sum_{z\in Z_{il}} (X_z^v + \bar{X}_z^v) \le U^v N^v, v \in S_{jk}^v \cap V_{jk} \qquad \text{(3-5)}$$

$$OY_z^p \ge X_z^p, p \in P_{ij}, z \in Z_{il} \qquad \text{(a)} \qquad \text{(3-6)}$$

$$OY_z^v \ge X_z^v, v \in V_{jk}, z \in Z_{il} \qquad \text{(b)}$$

$$OY_z^q \ge X_z^q, q \in Q_{kl}, z \in Z_{il} \qquad \text{(c)}$$

$$O\bar{Y}_z^p \ge \bar{X}_z^p, p \in P_{ij}, z \in Z_{il} \qquad \text{(d)}$$

$$O\bar{Y}_z^v \ge \bar{X}_z^v, v \in V_{jk}, z \in Z_{il} \qquad \text{(e)}$$

$$O\bar{Y}_z^q \ge \bar{X}_z^q, q \in Q_{kl}, z \in Z_{il} \qquad \text{(f)}$$

$$\sum_m \lambda_{mj} = \sum_{z\in Z_{il}} \sum_{p\in P_{ij}} X_z^p, j \in J \qquad \text{(a)} \qquad \text{(3-7)}$$

$$\sum_m \bar{\lambda}_{mj} = \sum_{z\in Z_{il}} \sum_{p\in P_{ij}} \bar{X}_z^p, j \in J \qquad \text{(b)}$$

$$\sum_{\acute{m}} \lambda_{\acute{m}k} = \sum_{z\in Z_{il}} \sum_{q\in Q_{kl}} X_z^q, k \in K \qquad \text{(c)}$$

$$\sum_{\acute{m}} \bar{\lambda}_{\acute{m}k} = \sum_{z\in Z_{il}} \sum_{q\in Q_{kl}} \bar{X}_z^q, k \in K \qquad \text{(d)}$$

$$t^p Y_z^p + t^v Y_z^v + t^q Y_z^q + \frac{\lambda_{mj}+\bar{\lambda}_{mj}}{\mu_j(\mu_j-\lambda_{mj})} + \frac{\lambda_{\acute{m}k}+\bar{\lambda}_{\acute{m}k}}{\mu_k(\mu_k-\lambda_{\acute{m}k})} + \frac{1}{\mu_j} + \frac{1}{\mu_k} \le DT_z, \qquad \text{(3-8)}$$

$$p \in P_{ij}, q \in Q_{kl}, v \in V_{jk}, z \in Z_{il}, j \in J, m \in M_j, k \in K, \acute{m} \in M_k \qquad \text{(a)}$$

$$t^p\bar{Y}_z^p + t^v\bar{Y}_z^v + t^q\bar{Y}_z^q + \frac{\lambda_{mj}+\bar{\lambda}_{mj}}{(\mu_j-\lambda_{mj}-\bar{\lambda}_{mj})(\mu_j-\lambda_{mj})} + \frac{\lambda_{\acute{m}k}+\bar{\lambda}_{\acute{m}k}}{(\mu_k-\lambda_{\acute{m}k}-\bar{\lambda}_{\acute{m}k})(\mu_k-\lambda_{\acute{m}k})} + \frac{1}{\mu_j} + \frac{1}{\mu_k} \le DT_z,$$

$p \in P_{ij}, q \in Q_{kl}, v \in V_{jk}, z \in Z_{il}, j \in J, m \in M_j, k \in K, \acute{m} \in M_k$ (b)

$\lambda_{mj} + \bar{\lambda}_{mj} \le OH_{mj}, j \in J, m \in M_j$ (a) (3-9)

$\lambda_{\acute{m}k} + \bar{\lambda}_{\acute{m}k} \le OH_{mk}, k \in K, \acute{m} \in M_k$ (b)

$\lambda_{mj} + \bar{\lambda}_{mj} < \mu_j, j \in J, m \in M_j$ (a) (3-10)

$\lambda_{\acute{m}k} + \bar{\lambda}_{\acute{m}k} < \mu_k, k \in K, \acute{m} \in M_k$ (b)

$X_z^p, \bar{X}_z^p, X_z^v, \bar{X}_z^v, X_z^q, \bar{X}_z^q, \lambda_{mj}, \bar{\lambda}_{mj}, \lambda_{\acute{m}k}, \bar{\lambda}_{\acute{m}k}, N^v \ge 0,$ (3-11)

$Y_z^p, Y_z^v, Y_z^q, \bar{Y}_z^p, \bar{Y}_z^v, \bar{Y}_z^q, H_{mj}, H_{\acute{m}k} \in \{0,1\}$

This bi-objective model aims to minimize the total cost and the total risk. The cost objective (3-1) contains inbound and outbound drayage costs, rail-haul cost, the fixed cost to operate different types of train services, and the equipment acquisition cost at multimodal terminals. The risk objective (3-2) represents the population exposure due to inbound and outbound drayage, intermodal trains in the network, and congestion of hazmat containers at intermodal terminals. To evaluate the congestion risk, we have used average number of hazmat containers waiting to be served, which is equal to hazmat arrival rate multiplied by average hazmat waiting time. Constraint (3-3) represents the transshipment function being performed by different terminals, while accounting for different types of intermodal train service in the network. Constraint (3-4) guarantees that each receiver's demands are satisfied. Constraint (3-5) evaluates the number of each train service needed. U^vN^v represents the capacity of a service type v, which is equal to the maximum number of containers hauled over each of its legs. For example, if a service has one intermediate stop, and therefore, is composed of two legs, each carrying 50 and 100 containers respectively, then $U^v N^v = max\ (50, 100) = 100$. Assuming the maximum length for each train (U^v) is 20 containers, five trains for that service are required to carry the containers. In other words, the number of trains for a particular service is determined by the service leg on which maximum number of railcars would have to be moved. Constraint (3-6) sets the indicator variables associated with different links, and this information is used in (3-8) to evaluate the feasibility of including that link in forming an intermodal chain. Constraint (3-7) ensures that the sum of the rates of hazmat and regular containers served on all equipment at each terminal are equal to related arrival rate. The nonlinear constraint (3-8) ensures that all shipments arrive at the customer location by the specified delivery-times. The travel time for a shipment is composed of inbound and outbound drayage time, travel time of intermodal train, average waiting and service time in terminals. Constraint (3-9) ensures that a request (hazmat or regular) can be allocated to a piece of equipment only if that equipment is purchased, while constraint (3-10) enforces queue steady-state conditions. The feasible domains of the decision variables are defined in (3-11).

3.5. Solution Procedure

As delineated in Section 3.4, because of the existence of the bilinear and trilinear terms in the objective function (average number of hazmat containers waiting in the queue) and the delivery time constraint (average waiting time of containers in terminals), the model is nonlinear and cannot be solved by classical optimization techniques. To handle the problem, we developed a hybrid recursive solution procedure and label it RTIM-heuristic (Figure 3-3).

Step 1: Randomly generate input traffic at each terminal (ITG).
Step 2: Each terminal: Non-dominated sorting genetic algorithm (NSGA II).

Initial Solutions

a) Randomly assign input traffic to available equipment & build chromosome.
b) Repeat a) 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"e.

Stopping Criteria

f) 1000 iterations.

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.

Figure 3-3: Summery of RTIM heuristic

Based on this procedure, at each iteration the input traffic of each intermodal terminal is first assigned using a ITG Heuristic. Then, a multi-objective genetic algorithm, NSGA-II, generates a set of possible arrival rates of equipment inside each terminal. Finally, for each possible case of arrival rates, the mathematical model discussed in section 3.4 is updated with the values of λ_{mj} to a linear model, and solved by using CPLEX. This procedure is repeated at each iteration until 500 consecutive iterations do not produce better solutions. Please note that, scenario generated at an iteration leads to tens of different LP files (feasible solutions) which should be run by CPLEX. Hence, in generating hundreds of scenarios, thousands of feasible solutions are investigated to achieve the final solution. Details of the main components are brought next.

3.5.1. Step 1: Input Traffic Generator (ITG)

ITG aims to calculate the input traffic of each intermodal terminal. Knowing all possible paths for each pair of shipment, the heuristic randomly selects one for each container and increases the input traffic of the terminals involved in the selected path by one unit. For example, assume there are three paths from Origin to Destination (Figure 3-4).

Path 1: Origin→B→C→D→Destination

Path 2: Origin→A→ D→Destination

Path 3: Origin→A→E→F→Destination

Based on ITG, for each hazmat (regular) container, we randomly select between path 1, 2 and 3. If path1 is selected, the hazmat (regular) traffic at terminals B and D increase by one unit (C is an intermediate with no handling operation inside); If path2 is selected, the input traffic of terminals A and D increase; otherwise, the input traffic of terminals A and F increases.

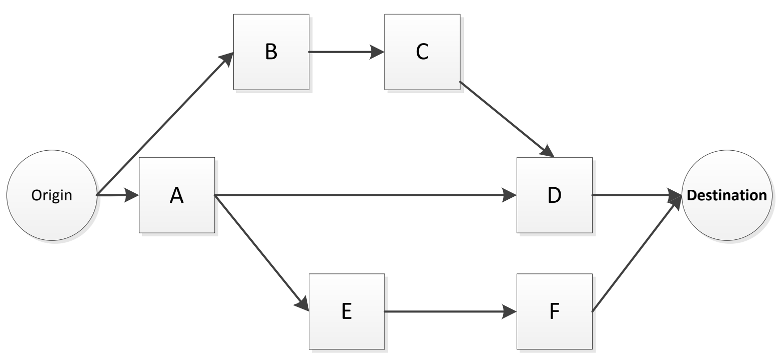


Figure 3-4: A sample network for ITG

Besides the scenarios generated using ITG, we consider an additional scenario achieved by solving our model without considering the operations inside the terminals. Ignoring the capacity planning part of the model, this scenario only makes routing decisions and thus determines the input traffic of the terminals.

3.5.2. Step 2: NSGA-II

To distribute the input traffic of each terminal among equipment and to determine the equipment arrival rates, we use Non-dominated Sorting Genetic Algorithm-II (NSGA-II) (Deb et al., 2002). NSGA-II is one of the most popular elitist multi-objective evolutionary algorithms (MOEAs), and is well known because of its good performance in solving large scale optimization problems.

NSGA-II functions as follows. First of all, an initial population P_0 of size N is created at random; and then the individuals in the population are ranked based on non-domination by using the following two steps. Please note that a solution is non-dominated if none of the objective function can be improved without worsening some of the other objective functions.

1. For each solution two things are calculated: the number of solutions that dominate the current solution (n_p) and a set of solutions that current solution dominates (S_p). The first non-dominated rank, which is also considered as the best rank, contains solutions with n_p equal to zero.
2. For every solution belonging to the first rank, we go to each member of its S_p and reduce its n_p by one. If n_p becomes zero, we add it to the second non-dominated rank. This process continues until all ranks are identified.

To acquire the related descendant populations Q_0, the primary population is undergone by crossover and mutation. For the generation *t*, a combined population of $R_t = P_t \cup Q_t$ is formed, and is then also sorted based on non-domination. Since R_t contains all the best non-dominated solutions from the beginning, elitism is ensured. In the next step, *N* best non-dominated solutions are selected from R_t for the new population P_{t+1}. If the number of the best solutions is less than *N*, the rest of individuals are selected from subsequent non-dominated ranks. In other words, to choose exactly *N* individuals, the solutions in the last accepted rank are sorted using crowding comparison operator in descending order and the best *N* individuals are selected. This procedure is repeated in each generation, until the best possible solution can be obtained based on a specific stopping criterion. In this study, maximum number of generations is considered the termination criterion and is set to 1,000.

3.5.2.1. Solution Representation and Initialization

In this study, we apply NSGA-II to determine the equipment arrival rates based on two conflicting objectives: “number of equipment” and “congestion exposure”. Given the nature of our problem, we present each solution as a simple string, whose length is two times the total number of available equipment in the network (see Figure 3-5).

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	$\bar{\lambda}_k^n$

Figure 3-5: Individual representation

In many meta-heuristics, the population of strings is initialized randomly at the beginning. However, for constrained problems, specific methods need to be applied to handle the constraints. In our case, three sets of constraints are preserved during the generation of individuals: the steady state constraint, the input traffic constraint, and the delivery time constraint. For the steady state constraint, the total sum of the hazmat and regular arrival rate of each piece of equipment has to be less than the service rate, e.g. $\lambda_{mj} + \bar{\lambda}_{mj} < \mu_j$. Secondly, the total sum of the hazmat/regular arrival rates of equipment inside each terminal should be equal to the hazmat/regular input traffic achieved by ITG, e.g. $\bar{\lambda}_{mj} + \bar{\lambda}_{\acute{m}j} + \cdots = \alpha_j$, ($\alpha$ is the set of terminals' input traffics calculated by ITG). Finally, we restrict the waiting time of the containers at the terminals to a specific time period (here we assumed one hour).

To handle the constraints in this study, we use a repair technique, which checks the individual chromosome for the violation of the constraints, and if necessary adjusts it. The repair method randomly assigns each container of the input traffic to an available crane and updates the free capacity of the selected crane by decreasing one unit. If the waiting time of the containers exceeds one hour, another piece of equipment will be selected. The population size is set to 100 in this research.

3.5.2.2. Selection Method and Reproduction Operators

To choose the parents for generating offsprings, we implement a binary-tournament selection method, where two individuals are randomly chosen and the fitter of the two is selected based on crowding comparison operator as a parent. This operator maintains diversity in the Pareto front. The selected chromosomes are subjected to a one-point crossover operator to generate offsprings. Here, we choose a terminal randomly. The starting point of the selected terminal in the array is the crossover point. All data beyond that point in either chromosome is swapped between the two parent organisms. The resulting chromosomes are the offsprings. Consider a network with two terminals, each of which has three pieces of equipment (Figure 3-6). Assuming the crossover point is 2, data belonging to terminal 2 (both hazmat and regular arrival rates) is swapped between the two parents.

	Terminal 1						Terminal 2					
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

Figure 3-6: Crossover

To maintain diversity from one generation of population to the next, a local search is used, in which a terminal is randomly selected, and its required number of equipment is changed. As illustrated in Figure 3-7, the selected terminal is terminal 1 with two pieces of equipment. The number of equipment is mutated to two, and the input traffic of this terminal is then randomly assigned to the three pieces of equipment. We choose the crossover probability of 0.8, which implies that the probability of a selected chromosome surviving to the next generation unchanged is 0.2. The mutation probability is set to 0.01.

	Terminal 1						Terminal 2					
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

Figure 3-7: Mutation

3.5.3. Step 3: CPLEX

After NSGA-II determines the arrival rate of each piece of equipment, the mathematical model developed in Section 3.4 is updated. Since the arrival rates are known, the bilinear and trilinear terms in the objective function and the delivery time constraint are linearized and the model can be solved by CPLEX. To call CPLEX in our C# application, we used ILOG CPLEX and ILOG Concert Technology for .NET users.

3.6. Computational Experiments

In this section, we discuss the estimation of the basic parameters of the model and then present the details of a real size problem to be solved by the proposed solution procedure in Section 3.6.2. Finally, we analyze the solution and provide detailed managerial insights.

Here we consider the intermodal service chain of Norfolk Southern in the US (Figure 3-8), including 19 intermodal terminals and 31 types of intermodal train services differentiated by route and intermediate stops. These train services connect 37 pairs of shipper/receivers distributed in different parts of the US. There are two types of train services, regular and priority, where the latter train type is 25% faster than the former one. The demand is randomly generated demand data utilizing the fuel oil consumption figures as compiled by the Department of Energy (2013) (http://www.eia.gov). To ensure each shipment to use both the road and rail, the generated demand data does not include a shipper and a receiver with access to the same terminal. We also consider the delivery time of 42 hours for each shipment and assume that there are 120 equipment items, with a service rate of 96 containers per day, 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.

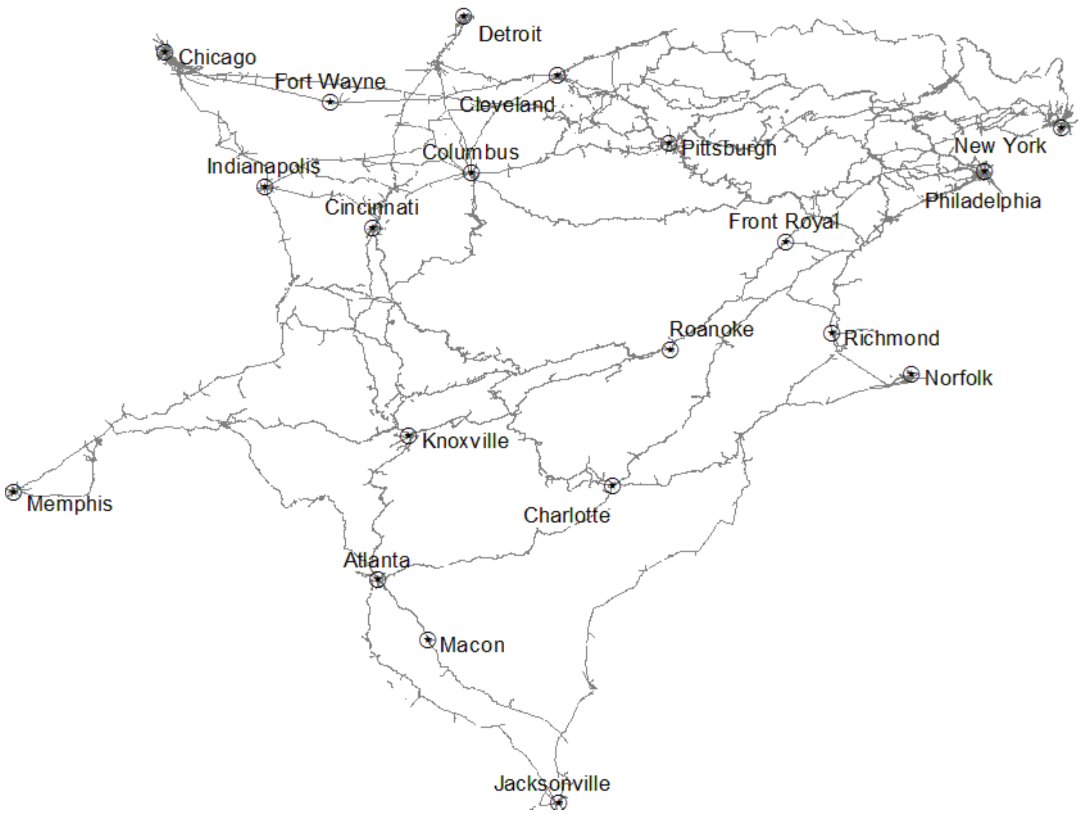


Figure 3-8: Intermodal rail services chain of Norfolk Southern (Adopted from Verma et al. (2012))

3.6.1. Parameter Estimation

3.6.1.1. Cost

The inbound drayage cost, intermodal rail-haul cost, fixed cost of operating intermodal train service, and outbound drayage cost are adopted from Verma et al. (2012). Detailed data is listed in Table 3-1. Based on the examination of current prices, we further assume \$35,000 to be the purchase cost of each piece of equipment.

3.6.1.2. Risk

To assess the population exposure caused by transportation through the inbound and outbound drayage and the rail-haul, we apply the traditional fixed bandwidth approach proposed by Batta and Chiu (1988) and ReVelle et al. (1991). In this approach, the population exposure is approximated by the total population in the rectangle shape impact area with a certain bandwidth that stretches along edge.

Table 3-1: Parameters

Drayage fuel charge	$250/hour
Average drayage speed	40 miles/hour
Intermodal rail-haul cost (regular)	0.875/mile
Intermodal rail-haul cost (priority)	1.164/mile
Fixed cost of running a intermodal train (regular)	$500/hour
Fixed cost of running a intermodal train (priority)	$750/hour

In evaluating the congestion exposure, we employ the method proposed by Erkut and Verter (1998), modeling the impact area as a danger circle with a radius centered at a terminal. Congestion exposure, regardless of type of hazmat, is the population inside a danger circle with a radius of 1 mile.

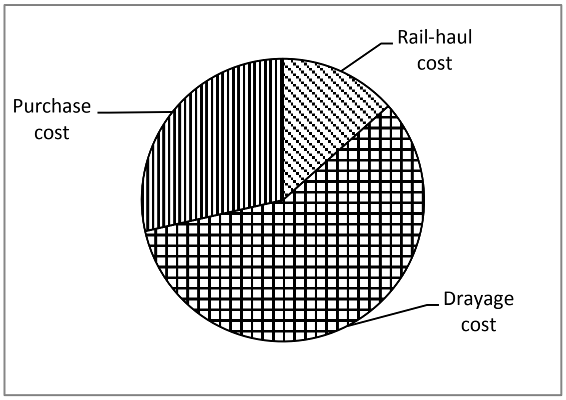
3.6.2. Solution and Discussion

To solve our suggested bi-objective model, we use the weighted sum method in which weights are attached to different objectives. This real-sized problem is first solved in a base case, where both objectives are equally important, i.e. each with a weight of 0.5. Further discussions regarding the trade-off between costs and risks can be found in Section 3.6.3.1. Please note that, for each problem we followed the procedure discussed in Section 3.5 and examined thousands of feasible solutions.

Table 3-2 provides the objective function values for the base case solution. The specified demand can be met by spending around $54.9 million, and exposing approximately 11.5 million individuals. Figure 3-9 presents the break-down of the costs and the risks. The major part of both cost and risk emerges from drayage operations. However, it is still necessary to consider the operations inside the intermodal terminals, as nearly 2.6 million people are exposed to the congestion risk at intermodal terminals, while totally $15.6 million is spent to purchase handling equipment. According to the base case solution, saving each extra individual from rail-haul, drayage and congestion risks costs $2.9, $5 and $6 respectively.

Table 3-2: Base case solution

Cost = $54,973,452			Risk = 11,503,674 people		
Rail-haul	Drayage	Purchase	Rail-haul	Drayage	Congestion
7,377,165	31,916,288	15,680,000	2,531,482	6,365,150	2,607,042



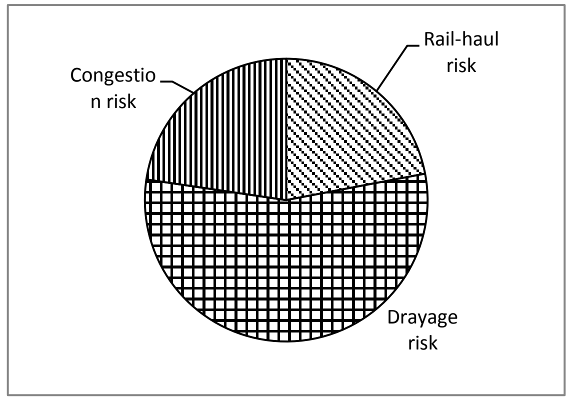


Figure 3-9: Proportions of costs and risks

Table 3-3 provides the relevant details on the 31 intermodal train services, where the maximum length for each train is 120 containers. For example, the first row refers to the intermodal train service that originates in Atlanta and terminates in Detroit, and has one stop in Knoxville.

A total of three regular trains are needed to move the specified containers, which would incur a fixed train cost of $188,491 and expose 46,391 people. Notice that four trains with origin or destination in New York and one train with destination in Memphis are not used, and the relevant traffic transited through Philadelphia and Atlanta respectively.

Table 3-3: Attributes of intermodal trains

From	To	Stops	Regular	Priority	Train Cost	Risk
Atlanta	Detroit	1	3	0	188,491	46,391
Atlanta	New York	1	1	0	84,848	20,125
Atlanta	Philadelphia	2	17	0	1,193,086	596,817
Atlanta	New York	1	0	0	0	0
Charlotte	Chicago	1	4	0	232,995	113,259
Charlotte	Detroit	1	4	0	233,184	66,934
Chicago	Philadelphia	1	2	0	106,971	50,337
Chicago	New York	0	0	0	0	0
Chicago	Charlotte	2	5	0	324,587	156,366
Chicago	Jacksonville	2	3	1	270,845	96,022
Cincinnati	Jacksonville	3	3	0	161,385	34,860
Columbus	Norfolk	1	5	0	204,242	74,723
Detroit	Philadelphia	2	2	0	112,567	38,587
Detroit	New York	1	1	0	5,730	5,060
Indianapolis	Philadelphia	2	4	0	239,106	107,704
Indianapolis	New York	1	1	0	31,080	12,160
Indianapolis	Atlanta	0	2	0	111,300	9,684
Jacksonville	Chicago	2	4	1	369,356	97,841
Jacksonville	Philadelphia	1	2	0	170,415	82,990
Memphis	Philadelphia	2	2	0	227,763	58,233
New York	Chicago	2	2	0	78,915	24,935
New York	Detroit	1	0	0	0	0
New York	Indianapolis	2	2	0	96,263	40,315
New York	Charlotte	1	4	0	112,980	96,348
New York	Atlanta	2	0	0	0	0
Philadelphia	Chicago	2	3	0	214,543	139,321
Philadelphia	Detroit	2	2	0	98,158	45,580
Philadelphia	Indianapolis	2	2	0	148,127	61,591
Philadelphia	Atlanta	2	12	0	722,363	351,554
Philadelphia	Jacksonville	1	5	0	243,600	103,745
Philadelphia	Memphis	1	0	0	0	0
Intermodal terminals		Regular	97			
		Priority		2		
		Fixed cost			1,394,265	
		Risk				2,531,482
Container routing					**5,982,900**	
Total			**97**	**2**	**7,377,165**	

Finally, Philadelphia, Atlanta and Charlotte are 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.

The capacity and congestion levels at intermodal terminals are presented in Table 3-4. This Table contains information about the number of purchased cranes, total purchasing cost, congestion risk and the average waiting time for the hazmat and regular containers. Figure 3-10 presents the congestion risk at different intermodal terminals. Among all the intermodal terminals, Philadelphia is of the highest congestion risks. According to Wikipedia, Philadelphia is the fifth most populated city in the United States with the population density of 11,380 mi^2. Moreover, it has the highest input traffic among all the intermodal terminals in the network, and keeps the hazmat containers waiting for 16.63 minutes on average. High population density besides the high service time makes Philadelphia the riskiest intermodal terminal.

The second place, Chicago, is the third most populated city in the United States with population density of 11,865/ mi^2, but because of its significantly lower input traffic, it is positioned after Philadelphia. Identifying factors affecting the congestion risk at intermodal terminals can help us avoid tragic events. This issue is discussed thoroughly in 3.6.3.2.

The average waiting times for hazmat and regular containers at intermodal terminals are presented in Figure 3-11. As we expected, since the priority queue is used to capture the congestion at terminals, the average waiting time of hazmat containers are considerably lower than that of regular containers. As the terminals are usually located in population centers in North America, the waiting time of containers (and consequently the average number of containers waiting in the queue) becomes more critical, when one considers hazmat freight. Improving a terminal's capacity by purchasing more or faster cranes decreases the waiting time and thus the congestion risk, significantly.

Table 3-4: Capacity and congestion at intermodal terminals

Intermodal Terminals	**Crane s**	**Purchasing Cost**	**Congestion Risk**	**Avg Haz Wait (min)**	**Avg Reg Wait (min)**
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	57.4
Columbus	22	770,000	102,158	16.47	55.76
Indianapolis	39	1,365,000	106,797	16.4	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	2,607,041		

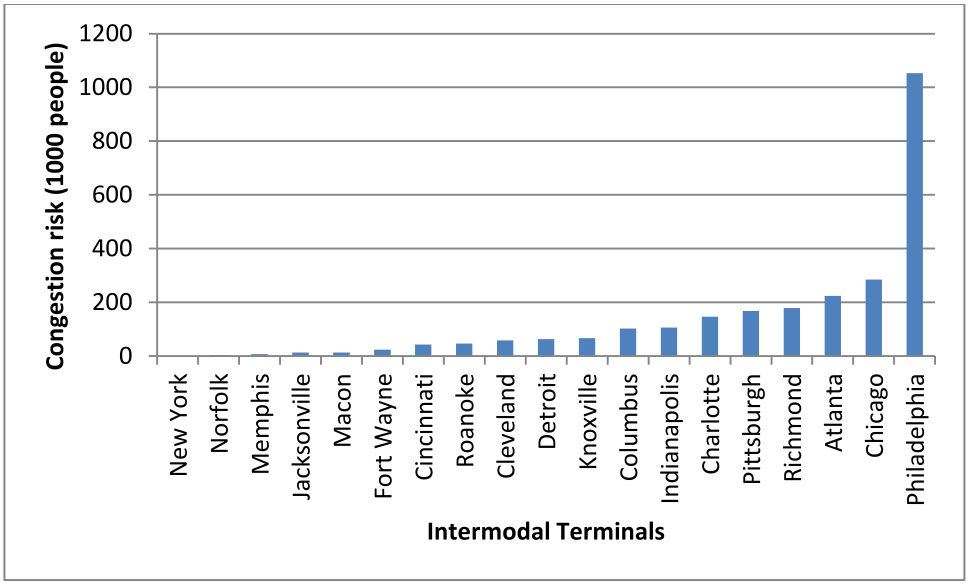


Figure 3-10: Congestion risk at intermodal terminals

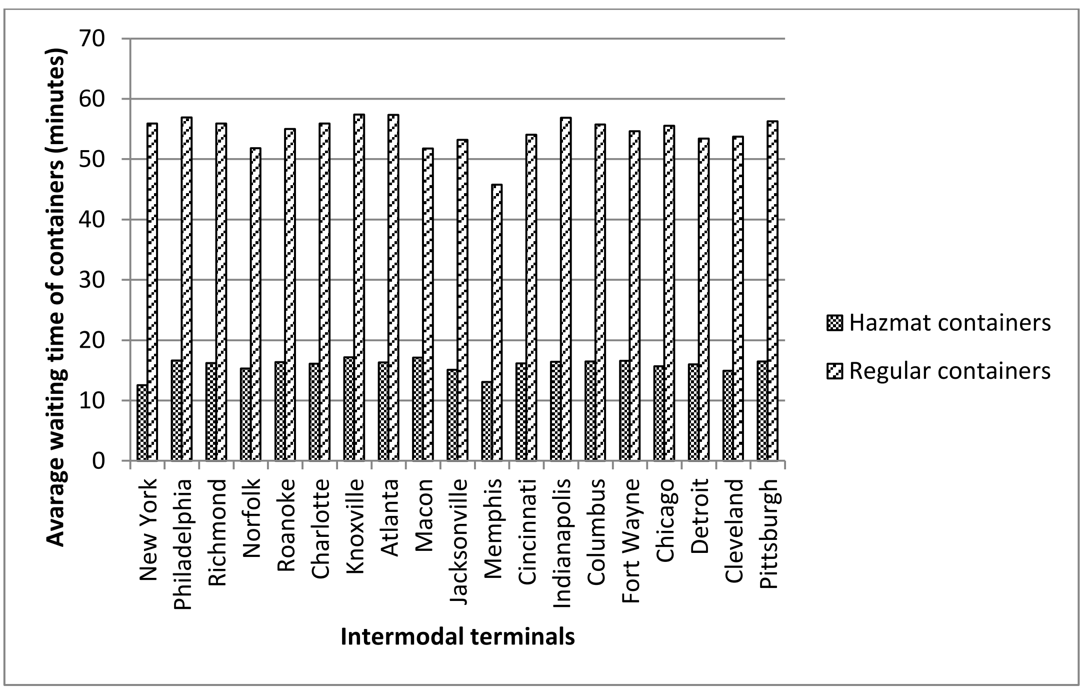


Figure 3-11: Average waiting time for hazmat containers at intermodal terminals

3.6.3. Managerial Insights

In this section, we approximate the Pareto optimal set by applying weighting method and iteratively varying the weights. We also investigate the congestion related issues inside intermodal terminals and analyze the system sensitivity as a function of delivery time and maximum waiting time parameters.

3.6.3.1. Risk-cost Trade-off

A base case (both of the weights are equal to 0.5) and several sensitivity analysis have been computed to better understand the tradeoff between the cost and the risk using our suggested multi-objective optimization model. Table 3-5 and Figure 3-12 present the results obtained by solving the model successively with varying weights.

Table 3-5: Alternative optimal solutions

	Cost ($)	Risk (people)	Cranes	Regular trains	Priority trains
Min cost	54,108,639	15,463,489	446	95	2
A = [Cost = 0.9, risk = 0.1]	54,356,576	13,226,310	450	95	2
B = [Cost = 0.8, risk = 0.2]	54,403,445	12,451,869	448	96	2
C = [Cost = 0.7, risk = 0.3]	54,609,014	12,263,181	452	96	2
D = [Cost = 0.6, risk = 0.4]	54,889,406	11,777,849	452	96	2
Base case	54,973,452	11,503,674	448	97	2
E = [Cost = 0.4, risk = 0.6]	55,553,671	11,024,551	448	98	2
F = [Cost = 0.3, risk = 0.7]	56,048,674	10,785,142	451	99	3
G = [Cost = 0.2, risk = 0.8]	56,522,751	10,629,767	451	101	3
H = [Cost = 0.1, risk = 0.9]	56,866,494	10,561,465	448	100	4
I = [Cost = 0.075, risk = 0.925]	56,965,014	10,554,690	450	102	3
J = [Cost = 0.05, risk = 0.95]	64,767,135	9,923,359	671	103	3
K = [Cost = 0.025, risk = 0.975]	72,977,475	9,524,539	905	102	4
L = [Cost = 0.02, risk = 0.98]	83,649,258	8,989,963	1,209	103	4
M = [Cost = 0.01, risk = 0.99]	102,222,454	8,912,949	1,738	103	7
Min risk	122,783,352	8,763,151	2,280	116	12

The min cost solution is 1.5% less expensive than the base case solution, but 34% more risky. The increment in risk is because of forcing drayage operations through shorter but more risky paths. On the other hand, the min risk solution is 100% more expensive but 23% less risky because of significantly less congestion at terminals and more priority trains. To minimize the congestion risk, all the terminals purchase all the 120 available cranes. In addition, the use of faster trains enables us to take longer but less risky drayages.

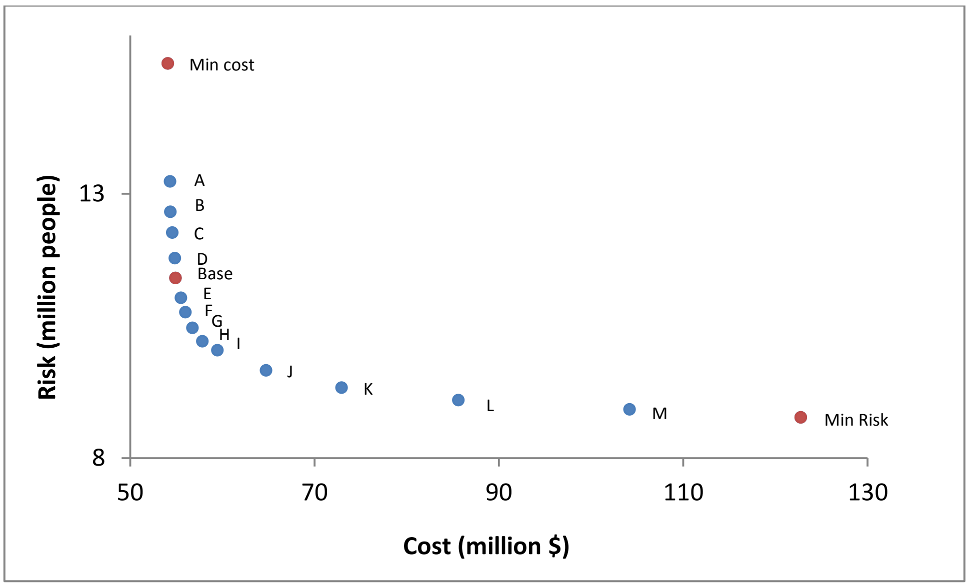


Figure 3-12: Weight based solutions

With regard to Figure 3-12, it is easy to see that risk reductions are achieved at small cost when moving from min cost to I, while risk reductions entails large costs for the rest of the solutions. The details of alternative solutions are presented in Table 3-6. Moving from min cost to min risk, rail and drayage risks decrease for 252,161 and 4,715,122 people respectively. The reductions in the risks are offset by 11% increase in both rail and drayage costs. In contrast to rail and drayage costs, the increases in the purchasing costs are significant, specifically when the risk coefficient exceeds 90%. Moving from I to min risk decreases the exposure for approximately 1.7 million people, however increases the cost for nearly $65.8 million, which means that the cost of exposing one fewer individual is $38.

Table 3-6: Solutions in detail

	Rail cost ($)	Drayage cost ($)	Purchasing cost ($)	Rail risk (people)	Drayage risk (people)	Congestion risk (people)
Min cost	7,390,589	31,108,050	15,610,000	2,751,923	10,169,604	2,541,962
A	7,365,707	31,240,869	15,750,000	2,615,082	8,024,127	2,587,101
B	7,372,602	31,350,844	15,680,000	2,577,283	7,276,046	2,598,540
C	7,366,402	31,422,613	15,820,000	2,543,650	7,110,230	2,609,301
D	7,361,400	31,708,006	15,820,000	2,537,027	6,651,368	2,589,454
Base case	7,377,165	31,916,288	15,680,000	2,531,482	6,365,150	2,607,042
E	7,388,352	32,485,319	15,680,000	2,500,414	5,928,101	2,596,036
F	7,477,992	32,785,681	15,785,000	2,481,513	5,720,313	2,583,316
G	7,529,844	33,207,906	15,785,000	2,478,889	5,575,511	2,575,367
H	7,588,625	33,597,869	15,680,000	2,473,751	5,490,359	2,597,355
I	7,598,827	33,616,188	15,750,000	2,487,840	5,473,003	2,593,847
J	7,614,666	33,667,469	23,485,000	2,490,873	5,466,227	1,966,259
K	7,629,675	33,672,800	31,675,000	2,492,337	5,463,563	1,568,639
L	7,643,252	33,691,006	42,315,000	2,496,827	5,457,457	1,035,679
M	7,713,948	33,678,506	60,830,000	2,499,762	5,455,314	957,873
Min risk	8,237,508	34,745,844	79,800,000	2,499,762	5,454,482	808,907

3.6.3.2. Congestion inside a Terminal

In an effort to get an insight into the congestion inside a specific terminal, we conducted two experiments. The first experiment investigates the impact of the number of cranes (capacity level) on the utilization rate and the service time, when the input traffic is constant. For this analysis, we considered the Norfolk terminal in the base case, min cost and min risk solutions. We chose Norfolk because its input traffic remained the same in the three aforementioned solutions. From Table 3-7, one sees that, as the risk coefficient increases from 0 (in min cost) to 1 (in min risk), the number of cranes increases significantly, which is balanced by the decrease in the congestion risk.

Table 3-7: Congestion at Norfolk terminal

	Cranes	Average hazmat waiting time (min)	Congestion risk	Average utilization rate
Min cost	7	17.42	3,705	0.75
Base case	8	15.32	3,690	0.65
Min risk	120	0.80	171	0.05

Another observation is the significant increase in the average utilization rate of cranes when the weight attached to the cost increases. Increasing the utilization rate of equipment (cranes) could be considered as a relevant goal for raising the terminal's productivity. However, as the utilization rate goes up, the service time goes up too. This means that there is a trade-off between reducing the service time and increasing the equipment's utilization. Finding a compromised solution might be of interest of the decision makers.

The second experiment aims to study the impact of increase in congestion exposure rate on the solution. We scaled the congestion exposure rate by 10 and compared the base case, min cost and min risk solutions. To mitigate the intensified congestion risk, two factors play important roles: input traffic (routing) and average hazmat waiting time (service time) (Table 3-8).

Table 3-8: Congestion at Philadelphia terminal

	Average hazmat waiting time (min)	Input hazmat traffic	Congestion Risk (people)
Min cost	16.51	2,313	8,794,197
Base case	5.54	1,424	2,031,124
Min risk	4.38	1,424	1,627,014

As the weight assigned to risk increases, the containers are routed away from the riskiest terminal (Philadelphia) and the relevant traffic transits through the nearest terminal, i.e. New York. Thus the number of train services originating at or transiting New York increases from 12 to 24 units. This observation implies that, routing regulations or even closing the routes that pass through the population centers can significantly improve public safety.

Hazmat waiting time is the second factor affecting the congestion risk. Comparing the min risk with the base case, we can see that the average hazmat waiting time directly influences the congestion risk. Decreasing the service time, fewer people are exposed to congestion risk (note that, the input traffics in these two solutions are equal). It is reasonable to conclude that improving the service time, by adding more or faster (higher service time) cranes, can significantly mitigate the public and environmental risk, specifically when there is no concern over budget.

3.6.3.3. Variation in Delivery Time

We also investigated the impact of variations in delivery time on the solution (Table 3-9). First, with T = 36, a larger number of cranes and priority trains are required, which increases purchasing and rail costs. The increment in the purchasing cost is compensated by reduction in the congestion risk. Second, with T = 48, fewer premium trains and cranes are needed, thereby resulting in lower rail and purchasing costs. The increase in the drayage risk in both cases of T = 36 and T = 48, is reimbursed by less drayage cost through taking more risky but shorter roads.

Table 3-9: Impact of delivery time (DTz)

Delivery Time (hr)	Cranes	Train		Cost (1000 $)			Risk (1000 people)		
		Regular	Premium	Rail	Drayage	Purchasing	Rail	Drayage	Congestion
T = 36	1,873	92	10	7,615	31,887	65,555	2,532	6,390	1,054
Base case (T = 42)	448	97	2	7,377	31,916	15,680	2,531	6,365	2,607
T = 48	447	99	0	7,369	31,892	15,645	2,497	6,389	2,587

3.6.3.4. Variation in Maximum Waiting Time

As we mentioned previously, we restrict the waiting time (WT) of the containers at the terminals to one hour. To examine the effect of increasing the maximum waiting time on the solution, we further considered two additional cases: WT = 3 hours and WT = 5 hours. According to Table 3-10, when we increase the maximum WT, fewer cranes but more premium trains are needed to serve. Purchasing fewer cranes leads to lower service level and consequently higher congestion risk. To compensate for the longer waiting time at intermodal terminals and preserve the delivery time, more premium trains are needed, resulting in higher rail cost.

Table 3-10: Impact of maximum waiting time (WT)

Waiting Time (hr)	Cranes	Train		Cost (1000 $)			Risk (1000 people)		
		Regular	Premium	Rail	Drayage	Purchasing	Rail	Drayage	Congestion
Base case (WT = 1)	448	97	2	7,377	31,916	15,680	2,531	6,365	2,607
WT = 3	374	97	3	7,409	31,911	13,090	2,530	6,364	3,607
WT = 5	358	95	6	7,472	31,922	12,530	2,524	6,365	3,908

3.7. Conclusion

In this study, a bi-objective model is suggested for transportation of regular and hazmat containers through the rail-truck intermodal network. With regard to stochastic nature of transportation, we present congestion as a source of population exposure caused by delays during the transportation of hazmat containers, more specifically, the waiting due to limited service capacity at intermodal terminals. To capture the congestion, each piece of equipment at intermodal terminals is modeled as a non-preemptive priority queue, where the hazmat containers are of higher priority than the regular ones. Because of the computational difficulties caused by non-linear terms, we further employ an iterative solution procedure incorporating a heuristic and a multi-objective genetic algorithm, to generate a linear model which could be solved by CPLEX. The model is then applied to a realistic problem instance.

This work contributes to the literature by the following aspects. First of all, this is the first work that incorporates uncertainty resulting from the uncertain nature of the hazmat transportation problems. Secondly, this research explicitly considers the congestion at intermodal terminals as a source of exposure in hazmat transportation problem, and applies the priority based queuing to handle the possible congestions. Furthermore, the suggested model incorporates capacity planning with the routing of hazardous materials in the congested networks. Finally, we study the tradeoff associated with the cost and the risk.

Our computational experiments show that besides the drayage and rail-haul, congestion at intermodal terminals is a main source of population exposure. Especially in the networks where the intermodal terminals are located in population centers, the transportation of hazmat freight can be very problematic. Improving the service time at busy terminals using more or faster handling equipment (e.g. cranes) and applying tighter routing regulations, or even closing the rail/road segments that pass through populated centers, can considerably mitigate the potential risk. In addition, the installation of adequate emergency response facilities in the bottlenecks of the network, and application of information technology to identify the contents involved in an accident should be the priorities of railroad industries. Finally, since the delivery time is a major concern for many companies, it is important to consider the impact of congestion (or capacity) of intermodal terminals on the supply (delivery) time.

The location of the intermodal terminals can considerably affect the transportation of hazardous materials, especially the total risk. One area for future research is to integrate the location problem with routing in the context of hazardous materials. Also, in this study, we modeled the congestion at each piece of equipment as a single server priority queue. For the future research, we can model the entire terminal, including multiple equipment items, as a multiple server priority queue.

This research helps decision makers identify the risky terminals and adopt appropriate reactive policies for risk management. To reduce the consequence of hazmat incidents *a priori*, proactive risk mitigation policies could be adopted. The next chapter focuses on the proactive policies regulating the use of intermodal terminals by hazmat carriers.

4. Regulating Intermodal Transportation of Hazardous Materials

Abstract: This research employs the bi-level programming approach to assist the government in regulating the usage of intermodal terminals for hazardous material transportation. A bi-level network design model and a bi-level bi-objective toll-setting policy model are proposed to mitigate the transportation risk. The application of our models is illustrated by a real problem instance based on the intermodal service chain of Norfolk Southern in the US. Computational experiments provide detailed managerial insights for different shareholders.

Keywords: Bi-level Programming; Network Design; Toll Policy; Rail-truck Intermodal; Hazardous Material; Particle Swarm Algorithm;

4.1. Introduction

Major part of hazmat freights are transported via road and rail, especially for long-distance shipments. For example, in the United States and Canada, rail carries approximately 1.8 million and 500,000 carloads of hazmat annually respectively (AAR, 2006 and TSB, 2004). The trend of transporting hazmat by rail is expected to continue in the future, due to the development of rail-truck intermodal transportation (RTIM) networks and the claims that rail is the safest way to move hazmat. According to the US Department of Transportation, within the 12 years from 1994 through 2005, hazardous materials released in railroad accidents resulted in a total of 14 fatalities, while in the same period, hazardous materials released in highway accidents resulted in a total of 116 fatalities (Federal Railroad Administration, 2014). However, recent railroad incidents in Canada and the United States shattered rail industries' claims about safety and reignited debates about risks. In the fourth deadliest rail accident in Canadian history in July 2013, a 74-car freight train carrying crude oil ran away and derailed. Forty-seven people were confirmed dead, 2000 people were evacuated, and $50 million was claimed to insurance companies (CBC, 2013). In 2013, there were more than 16,000 incidents related to hazmat transportation in the United States, most of which involved flammable-combustible liquid and corrosive materials

Because of the health and environmental risks associated with transportation of hazmat, this domain is regulated by the government. In the United States, the Pipeline and Hazardous Materials Safety Administration (PHMSA) is responsible for the safe and secure movement of shipments of hazardous materials by all modes of transportation. In Canada, this is Transport Canada's responsibility to develop safety standards and regulations in the transportation of dangerous goods. Despite extraordinary growth of hazmat shipments, the regulatory oversights and safety measures have not been changed very much. Mounting instances of hazmat derailments necessitates a tighter regulation by the governments.

In this study, we consider two intermodal network design and toll-setting regulations which restrict the usage of certain terminals such that the overall system risks are minimized. The importance of utilizing a new regulation for the location of intermodal terminals is due to the substantial impact of those locations on the routing decisions, and hence on the risk issues. Based on these regulations, the carrier company makes routing decision in a RTIM network (for discussion on RTIM networks see Section 3.1).

The carrier's problem is to identify the routes between the origins and destinations for hazmat shipments in an RTIM network that minimizes the costs and satisfies the customer specified delivery times. This research considers two costs: 1) the transportation cost of the three portions of the intermodal transportation chain, and 2) the fixed cost of opening and maintaining a certain train service. Among the aforementioned costs, the drayage cost is a function of time the crew is engaged and the estimated consumed fuel. The rail-haul cost depends on the type of the service, in our case, either regular or priority. In addition to the rail-haul cost and regardless of the number of cars assigned to a train, there is a fixed cost for operating a train service that mainly consists of the wages of the train crews.

The concern of government is different from the carrier company when it comes to the transportation of hazmat freights. The government aims to identify ways to manage and reduce the risk of a hazmat transportation operation by designing a network or imposing tolls on terminals, such that the total risk resulting from the carriers' route choices is minimized. Herein, the total risk is measured in terms of population exposure and consists of the transportation risk through the inbound drayage, rail-haul and outbound drayage.

The population exposure refers to the total number of people exposed to the undesirable consequence due to the movement of hazmat containers.

Because the decision makers in our problem belong to two different levels of hierarchy and have conflicting objectives, the traditional single level optimization model is no longer applicable. One of the common methods to solve decentralized planning problems is the bi-level programming approach, which contains two levels of optimization, the upper level (leader) and the lower level (follower). The feasible region of upper level problem is determined by its own constraints and the lower problem.

In this research, we develop an intermodal network design approach (INDA), where, at the upper level, the government designs the rail-truck intermodal network by making decision about the terminals that should be closed, and carrier then selects among available route choices at the lower level and in turn determines the transportation risk. More specifically, the government restricts the amount of hazmat freights transporting through the intermodal network, without imposing certain routes to the carrier. Please note that, due to the closure of some terminals, a number of demands may remain unsatisfied, thus we consider a set of inbound and outbound drayage segments for possible construction by the government.

Despite the effectiveness in mitigating risks, the network design approach is considered to be rigid due to its ignorance of carrier's priorities and the waste of available infrastructure resources (Wang et al., 2012). Therefore, we further propose a bi-level bi-objective toll-setting policy model (BOTP), in which the government deters the carrier from using certain terminals via assigning a toll to each hazmat container passing through those terminals. The carrier's concern, i.e. the lower level, is still a routing problem to minimize the total transportation cost; while the government's perspective, i.e. the upper level, is formulated as a bi-objective optimization model, where the first objective is to minimize the overall system risk, and the second objective is to minimize the total toll value. Please note that, in spite of being revenue to the government, the total toll value is minimized because the government essentially aims to reduce the hazmat transportation risk, and thus would like to encourage the carrier to cooperate with this policy.

The main contribution of this study is the proposed bi-level models for the design and management of rail-truck intermodal network. As far as we know, this is the first time that the bi-level programming approach has been developed for the regulation of an intermodal network. In general, the problem that we study in this research has the following characteristics: *first*, there are two decision makers (government and carrier) at two levels of administration. *Second*, the two decision makers make their decisions sequentially, i.e. the government executes its decision prior to the carrier. *Third*, although government and carrier optimize their objective functions independently of each other, their objective functions and feasible regions are affected by the decisions made by the other side.

The remainder of this chapter is organized as follows. Section 4.2 provides a thorough review of the relevant literature. Section 4.3 proposes INDA and discusses the solution procedure. A numerical experiment is conducted with real-world data. Section 4.4

presents BOTP, and introduces a multi-objective PSO solution method. The two approaches are compared, and managerial insights are provided in Section 4.5. Finally, section 4.6 concludes this chapter with contributions and possible future research directions.

4.2. Literature Review

In the following we review the literature in multi-level hazmat transportation. Hazmat transport network design is a young domain of research that began to be seen as a separate field of study after the seminal paper of Kara and Verter (2004), which was the first paper that addressed the relationship between the government and the carriers in designing a road network for hazmat transportation. At the upper level, government aims to identify the road segments that should be closed to minimize the risk of transportation, while, at the lower level, the carrier company chooses the cheapest routes among those available to move the shipments. The bi-level model was converted to a single-level model by replacing the lower level problem by the KKT conditions of its LP relaxation. Erkut and Gzara (2008) generalized the model developed by Kara and Verter (2004) with the consideration of undirected road segments, and extended the problem to a bi-objective bi-level model by including cost in the objective function of upper level problem. They proposed a heuristic solution method to solve the problem. Another bi-level hazmat network design model was developed by Bianco et al. (2009). At the outer level problem, the government minimizes the maximum link risk over populated links of the whole network, i.e. risk equity, and, at the lower level, there is the regional area authority that minimizes the total risk over the network. Applying KKT conditions, the model was solved by transforming to a single-level problem. Since the achieved optimal solution may not be stable, they also suggested a heuristic algorithm to ensure a stable solution. More recently, Gzara (2013) suggested a method to solve bi-level hazardous material transport network design problems. Based on infeasible solutions, the method first constructs bi-level feasible solutions, and then a set of valid cuts is identified and incorporated within an exact cutting plane algorithm. Toll setting was suggested by Marcotte et al (2009) as an alternative policy tool to regulate the use of roads for hazmat freight. They developed a bi-level model, in which, at the upper level, the government sets tolls on network links to minimize the total risk and the total carriers' transportation cost, while the carrier selects the routes to minimize the transportation cost at the lower level. To solve the model, the bi-level problem was reduced to a single level mixed integer model using primal-dual constraints. Assuming both hazmat traffic and regular traffic affect population safety, Wang et al. (2012) suggested a dual toll setting model to mitigate the risk. The formulated bi-level model was then reduced to a two-stage problem in which the first stage problem was solved by the branch and bound and the null space active set method, and the second stage problem was solved using linear programming techniques. More recently, Bianco et al. (2012) developed a toll setting policy that minimizes the network total risk and achieves the risk equity. They also assumed that the toll paid by a carrier on a segment depends on the usage of that link by all carriers, and thus formulated the lower level problem as a Nash game. To solve the problem, a local search algorithm was proposed to heuristically explore the leader's search space in order to evaluate the effectiveness of the leader's choice.

All existing multi-level hazmat network design studies consider exclusively road networks, which are very different from intermodal rail-truck networks in terms of infrastructure, operations, and level of administration. First, from the infrastructure perspective, rail-truck intermodal networks consist of drayages, rail-haul, and intermodal terminals in which freights are transferred between two modes. The location of the terminals affects the routing decisions and the risk of transportation, thus combined location routing models are more demanded in such networks. Secondly, the operations of a road network and a rail network have significant differences due to the properties of the two transportation modes. As a combination of the two, a rail-truck intermodal network requires more comprehensive operations. This fact causes the lower level problem to be more complicated than a model involves only the road mode.

Finally, as to the level of administration, unlike the single mode road networks, the rail-truck intermodal networks have stakeholders, i.e., the intermodal carrier, in addition to the government. The interests of both stakeholders definitely should be taken into account when making decisions.

Because of these fundamental differences between these two types of the networks, the existing models cannot be effectively applied to our setting. Thus, here we propose bi-level models for regulation of a rail-truck intermodal network for hazmat transportation, with regard to the characteristic features of the rail-truck intermodal networks.

4.3. The Intermodal Network Design Approach (INDA)

4.3.1. Problem Description

Based upon the hierarchical decision making, our research aims to answer the following question at the upper level (government):

Which intermodal terminal should be closed to mitigate the transportation risk?

The following two questions at the lower level (carrier):

1) How many intermodal train services should be maintained between the available terminals?
2) How to route hazmat containers to their destinations through the available terminals at the lowest cost?

The facility location and routing decisions are strictly interrelated, especially when hazmat freights are concerned. The selection of terminal locations implies the selection of routes, and thus affects the transportation risk.

Under this policy, the government selects the intermodal terminals that should be closed to mitigate the human and environmental risk associated with the transportation of hazmat containers. The amount of hazmat flowing through the network is thus restricted by not imposing specific terminals and routes to the carrier. After the available terminals are identified by the government as the leader, the carrier executes its policies in light of the government's decision and determines the number of train services and the routing of the containers. Figure 4-1 presents the schematic view of our network design problem. Note that, differently from the model of Kara and Verter (2004), in our model, the leader (the government) selects the intermodal terminals that should be closed to hazmat freights, rather than the road segments. It is obvious that the rail and road segments originating from or terminating in a closed terminal are considered closed too. In addition, at the lower level, the carrier not only makes the routing decisions on the available network, but also determines the number of different types of train services needed.

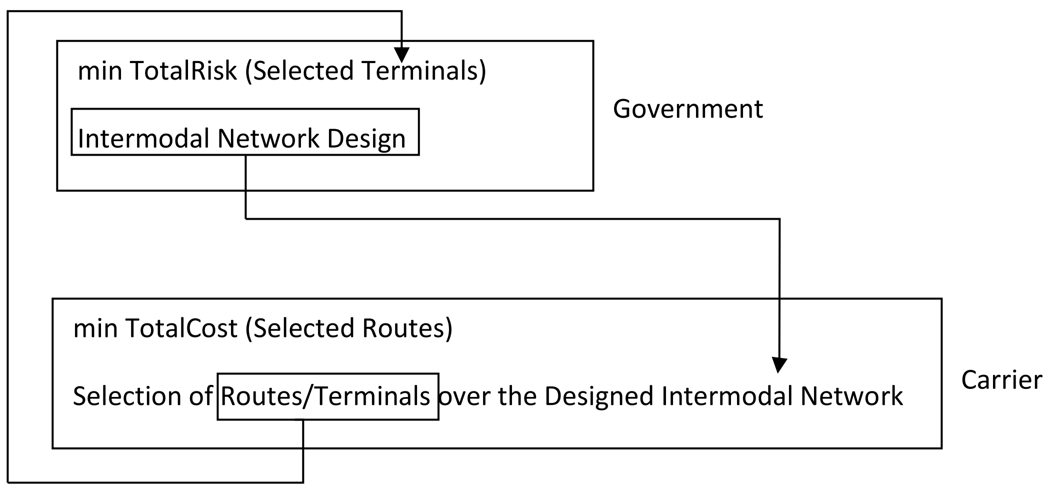


Figure 4-1: Schematic view of INDA

Since closing some terminals makes a number of existing intermodal routes infeasible, we consider a set of inbound and outbound drayage links for possible construction, and therefore preserve the connectivity of the network. In addition, it is assumed that, closing an origin or destination terminal of a train service does not make the entire service unavailable, unless there is no intermediate stop. If the origin (terminal) of the service is closed, then the first intermediate stop is considered as the origin, and if the destination (terminal) of the service is closed, then the last intermediate stop is considered as the destination. For example, consider a service that originates in *A* and terminates in *D*, and has two stops in *B* and *C*. If *A* is closed, then *B* is regarded as the origin of the service; and if *D* is closed, then *C* is regarded as the destination of the service.

4.3.2. Model Formulation

We formulate the INDA model based on the following notation.

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 traffic-classes, indexed by z. The elements of this set are derived from pairing every shipper $i \in I = \{1, 2, . . . , a\}$ with the receiver $l \in L = \{1, 2, . . . , f\}$ it supplies
P_{ij}	Set of inbound drayage between each shipper $i \in I = \{1, 2, . . . , a\}$ and each origin terminal $j \in J = \{1, 2, . . . , b\}$, indexed by p
Q_{kl}	Set of outbound drayage between each destination terminal $k \in K = \{1, 2, . . . , e\}$ and each receiver $l \in L = \{1, 2, . . . , f\}$, indexed by q
V_{jk}	Set of intermodal train services between each terminal pair j-k, where $j \in J = \{1, 2, . . . , b\}$ and $k \in K = \{1, 2, . . . , e\}$, indexed by v

S_{jk}^{v} Set of train service legs for intermodal train service type *v* operating between terminals $j \in J = \{1, 2, . . . ,b\}$ and $k \in K = \{1, 2, . . . ,e\}$, indexed by *s*

Input parameters:

O A large number

C^{p} Cost of moving one hazmat container on path *p* for inbound drayage

C^{v} Cost of moving one hazmat container using intermodal train service of type *v*

C^{q} Cost of moving one hazmat container on path *q* for outbound drayage

FC^{v} Fixed cost of operating intermodal train service of type *v*

E^{p} Population exposure due to moving one hazmat container on path *p* for inbound drayage

E^{v} Population exposure due to moving one hazmat container on intermodal train service of type *v*

E^{q} Population exposure due to moving one hazmat container on path *q* for outbound drayage

t^{p} Inbound drayage time using path *p*

t^{v} Travel time of intermodal train service of type *v*

t^{q} Outbound drayage time using path *q*

DT_{z} Delivery time associated with traffic-class *z*

U^{v} Maximum number of containers that can be loaded on intermodal train service of type *v*

D_z Number of hazmat containers demanded in traffic-class *z*

Decision variables:

X_z^p Hazmat containers of traffic-class *z* using path *p* for inbound drayage

X_z^v Hazmat containers of traffic-class *z* on train service of type *v*

X_z^q Hazmat containers of traffic-class *z* using path *q* for outbound drayage

Y_z^P 1 if $X_z^p > 0$; 0 otherwise

Y_z^v 1 if $X_z^v > 0$; 0 otherwise

Y_z^q 1 if $X_z^q > 0$; 0 otherwise

h_j 1 if origin terminal *j* is open; 0 otherwise

h_k 1 if destination terminal *k* is open ; 0 otherwise

N^v Number of intermodal train service of type *v*

$$\min_{h_j, h_k \in \{0,1\}} \sum_{z \in Z_{il}} \sum_{p \in P_{ij}} E^p X_z^p + \sum_{z \in Z_{il}} \sum_{q \in Q_{kl}} E^q X_z^q + \sum_{z \in Z_{il}} \sum_{v \in V_{jk}} E^v X_z^v \qquad (4\text{-}1)$$

where X_z^p, X_z^q and X_z^v solve:

$$\min \sum_{z \in Z_{il}} \sum_{p \in P_{ij}} C^p X_z^p + \sum_{z \in Z_{il}} \sum_{q \in Q_{kl}} C^q X_z^q + \sum_{z \in Z_{il}} \sum_{v \in V_{jk}} C^v X_z^v + \sum_{v \in V_{jk}} FC^v N^v \qquad (4\text{-}2)$$

s.t.

$$\sum_{p \in P_{ij}} X_z^p = \sum_{v \in V_{jk}} X_z^v, j \in J, z \in Z_{il} \quad (4\text{-}3.a)$$

$$\sum_{v \in V_{jk}} X_z^v = \sum_{q \in Q_{kl}} X_z^q, k \in K, z \in Z_{il} \quad (4\text{-}3.b)$$

$$\sum_{q \in Q_{kl}} X_z^q = D_z, z \in Z_{il} \quad (4\text{-}4)$$

$$\sum_{z \in Z_{il}} X_z^v \leq U^v N^v, v \in S_{jk}^v \cap V_{jk} \quad (4\text{-}5)$$

$$O h_j \geq X_z^v, v \in V_{jk}, z \in Z_{il} \quad (4\text{-}6.a)$$

$$O h_k \geq X_z^v, v \in V_{jk}, z \in Z_{il} \quad (4\text{-}6.b)$$

$$O Y_z^p \geq X_z^p, p \in P_{ij}, z \in Z_{il} \quad (4\text{-}7.a)$$

$$O Y_z^v \geq X_z^v, v \in V_{jk}, z \in Z_{il} \quad (4\text{-}7.b)$$

$$O Y_z^q \geq X_z^q, q \in Q_{kl}, z \in Z_{il} \quad (4\text{-}7.c)$$

$$t^p Y_z^p + t^v Y_z^v + t^q Y_z^q \leq DT_z, p \in P_{ij}, q \in Q_{kl}, v \in V_{jk}, z \in Z_{il}, j \in J \quad (4\text{-}8)$$

$$X_z^p, X_z^v, X_z^q, N^v \geq 0, \quad (4\text{-}9)$$

$$Y_z^p, Y_z^v, Y_z^q \in \{0,1\}$$

Equation (4-1) is the government's problem which aims to minimize the population exposure caused by the inbound and outbound drayages and intermodal trains in the network. Decision variables h_j and h_k are passed to the lower level problem as inputs. Equations (4-2)-(4-9) represent the carrier's problem which determines the routing of the containers through available intermodal terminals, such that the total cost is minimized.

The cost objective (4-2) contains inbound and outbound drayage costs, rail-haul cost and the fixed cost to operate different types of train services. Constraint (4-3) represents the transshipment function being performed by different terminals, while accounting for different types of intermodal train service in the network. Constraint (4-4) guarantees that each receiver's demands are satisfied. Constraint (4-5) evaluates the number of train services needed. $U^v N^v$ represents the capacity of a service type v, which is equal to the maximum number of containers hauled over each of its legs. For example, if a service has one intermediate stop, and therefore, is composed of two legs, each carrying 50 and 100 containers respectively, then $U^v N^v = max\ (50, 100) = 100$. Assuming the maximum length for each train (U^v) is 20 containers, five trains for that service are required to carry the containers. In other words, the number of trains for a particular service is determined by the service leg on which maximum number of railcars would have to be moved. Constraint (4-6) guarantees that a container can enter a terminal only if that terminal is open. Constraint (4-7) sets the indicator variables associated with different links, and this information is used in (4-8) to evaluate the feasibility of including that link in forming an intermodal chain. Constraint (4-8) ensures that all shipments arrive at the customer location by the specified delivery-times and is composed of inbound and outbound drayage time and the travel time of intermodal train. The feasible domains of the decision variables are defined in (4-9).

4.3.3. Solution Procedure

Finding a global solution to a bi-level model may not be easy since solving the upper level objective function requires evaluation of the lower level problem. Here, we discuss three common solution methods used to solve bi-level problems.

Enumeration method: this method is based on the fact that the extreme point of the high level decision maker's solution space is also an extreme point of the lower level feasible region (Wen and Hsu, 1991). There is a wide class of methods for solving linear bi-level optimization work based on enumeration technique. One of the first solution procedures built on enumeration was suggested by Candler and Townsley (1982). They showed that, when an optimal solution for the lower level problem is reached, changing the leader's decision variable would not affect the solution's optimality, but only impact its feasibility. Based on this finding, they developed an algorithm that evaluates the extreme points in search for the global optimal solution. The main drawback of the algorithm is that it cannot well solve a linear bi-level programming problem when the upper level's constraints are in the arbitrary linear form. In addition, occasionally an unacceptably long time may be needed before a solution is found.

Karush–Kuhn–Tucker method: in this method, the lower level problem is replaced with its Karush–Kuhn–Tucker (KKT) conditions . As the result, the bi-level programming model is transformed into a single-level problem. The resulting problem falls into a group of very hard problems, called mathematical programs with complementarity constraints. Kara and Verter (2004) and Bianco et al. (2012) are two of the papers applying KKT for hazmat transportation. It is important to note that KKT is not an appropriate solution for bi-level problems with integer or binary variables, which is exactly the case in our research.

Heuristic method: different heuristic methods have been suggested to solve bi-level models in the literature. There are two major groups of heuristic methods. The first group is those approximating the reaction function. Reaction function can be defined as the user equilibrium[1] with the decisions made by the leader. An example of this group of heuristic methods is sensitivity analysis based (SAB) algorithms, which has been used for solving bi-level transportation models (Yang and Yagar, 1994). Using the derivative information obtained from sensitivity analysis, SAB formulates a local linear approximation of the upper level objective function and the implicit, nonlinear constraints. The resulting linear model can be solved using simplex. Thus, SAB is a sequence of linear approximations to the original problem (Yang et al., 1994). The weakness of this algorithm is that the resultant converged solution might not be a global optimum.

The second group is the meta-heuristics approaches that have generated interest in the research community as an alternative for solving bi-level problems. Mathieu et al. (1994), Yin (2000) and Marinakis and Marinaki (2008, 2013) are some of the papers using meta-heuristics to solve bi-level problems. Since our model is mixed integer, the exact solution methods either cannot find the global optimum or are computationally inefficient for solving real size problems. So we employ a particle swarm optimization (PSO) to solve

[1] For a fixed vector of leader's decision, we consider a state as equilibrium if no follower can improve his or her utility by unilateral deviation.

our bi-level model. We chose PSO, because it is easy to implement while is capable of finding near optimal solutions within a reasonable time. The influence of particles on each other in their evolution enables PSO to handle high dimensional problems.

4.3.3.1. Particle Swarm Optimization Algorithm

Particle swarm optimization simulates the movement of bird flocking or fish schooling as a search method. As a population-based search technique, PSO enjoys rapid convergence while being computationally simple. It was first introduced by Kennedy and Eberhart (1995), and since then has been successfully applied to combinatorial optimization problems. According to the procedure suggested by Kennedy and Eberhart, particles, each representing a feasible solution, collaborate in finding the best solution/position. Searching for the best position, each particle adjusts its position according to the velocity. Scientists found that the synchrony of flocking behavior was through maintaining optimal distances between individual members and their neighbors. Thus, velocity plays the important role of adjusting each other for the optimal distance (Liao et al., 2007). A particle's velocity is a function of the particle's best previous position (*pbest*) and the whole swarm's previous best position (*gbest*) (details see Section 4.3.3.4). Thus, the shared information among particles, that are neighbors of each other, leads them to the best position in the search space.

The algorithm starts with creating a set of particles, whose positions and velocities are randomly initialized. Then, through a number of iterations, the velocities and the positions are updated. The personal best (*pbest*) and global best (*gbest*) positions are used for updating each particle's velocity. To enhance the global search capability of the particles, we equip PSO with a mutation operator. After mutating the particles, their fitness values are evaluated. The fitness of each particle (the total cost) and the total risk of transportation are determined by solving the lower level problem. The lower the total cost is, the better the corresponding position is. Based on the new fitness values, *pbest*s and *gbest* are updated. In this research, the maximum number of iterations is considered as the termination criterion and is set to 500.

4.3.3.2. Particle Representation and Initialization

The PSO that we develop for INDA codes the decision variables of the upper level problem as a particle and evaluates the fitness of each particle by solving the lower level. The search space for our problem is n-dimensional, where n is equal to the total number of origin and destination intermodal terminals in the network. Thus, our developed PSO is based on a binary representation, in which the solution structure is a one-dimension array of 0 and 1, which shows the availability of terminals (see Figure 4-2). The initialization of the population is made by randomly generating the particles with the primary velocities of 0, as much as the population size 20.

Origin terminals				Destination terminals			
h_1	h_2	…	h_b	h_1	h_2	...	h_e

Figure 4-2: Individual representation

4.3.3.3. Fitness Function

In this research, the fitness of each particle is evaluated by optimally solving the lower level problem. Based on the values of the upper level decision variables (h_j and h_k), the linear programming (LP) file of the lower level problem is updated (constraint 4-6) and solved by ILOG CPLEX. The fitness of each particle is equal to the total risk of transportation of the hazmat containers through the available terminals. Please note that, where ties occur amongst lower level solutions, we assume that the carrier chooses the routes that are favorable to the government. To call CPLEX in our C# application, we used ILOG CPLEX and ILOG Concert Technology for .NET users.

4.3.3.4. Particle Velocity and Position

During the iterations of PSO, a particle adjusts its position according to the velocity. The search space for our problem is n-dimensional, so rth particle can be presented by an n-dimensional vector $Pos_r = \{pos_{r1}, pos_{r2} \ldots pos_{rn}\}$ and $Vel_r = \{vel_{r1}, vel_{r2} \ldots vel_{rn}\}$. The velocity and positions of particles are calculated as follows:

$$vel_{r,s}^{g} = wvel_{r,s}^{g-1} + b_1 c_1 (pbest_{r,s}^{g-1} - pos_{r,s}^{g-1}) + b_2 c_2 (gbest_{r,s}^{g-1} - pos_{r,s}^{g-1}) \quad (4\text{-}10)$$

$$pos_{r,s}^{g} = pos_{r,s}^{g-1} + vel_{r,s}^{g} \quad (4\text{-}11)$$

$$1 \leq r \leq m, 1 \leq s \leq n, 1 \leq g \leq k \quad (4\text{-}12)$$

where m, n and k are the number of particles in the swarm, the dimension of search space and the maximum number of iterations, respectively. b_1 and b_2 are two random numbers between (0, 1), while c_1 and c_2 are the acceleration coefficients that lead the particle toward *pbest* and *gbest*. w stands for the inertia weight which controls the effect of previous velocity on the current velocity. The smaller values of w achieve the local exploitation, while the global exploration is attained by its larger values. Having run our algorithm multiple times, values of parameters have been set. m, n and k are set to 20, 19 and 500 respectively. c_1, c_2 and w are calculated for each particle at each iteration as follows:

$$c_1 = c_{1Min} + rand\ () * (c_{1Max} - c_{1Min}),\ c_{1Min} = 1.5,\ c_{1Max} = 2.5 \quad (4\text{-}13)$$

$$c_2 = c_{2Min} + rand\ () * (c_{2Max} - c_{2Min}),\ c_{2Min} = 1.5,\ c_{2Max} = 2.5 \quad (4\text{-}14)$$

$$w = w_{Min} + rand\ () * (w_{Max} - w_{Min}),\ w_{Min} = 0.1,\ w_{Max} = 1.0 \quad (4\text{-}15)$$

4.3.3.5. Mutation Operator

A mutation operator is used to improve the performance of the algorithm by avoiding local convergence. We use bitflip mutation where the value of a randomly selected bit is inverted (0 changes to 1, and 1 changes to 0). The mutation probability is set to 0.01, which implies that the probability of a selected particle surviving to the next iteration unchanged is 99%. Figure 4-3 shows the pseudocode of the developed PSO.

```
Initialize swarm
while iteration < maxIteration
        Update velocity of particle r
        Update position of particle r
        Apply bitflip mutation
        Evaluate the fitness function using CPLEX
        Update pbest and gbest
end while
```

Figure 4-3: Pseudocode of the developed PSO

4.3.4. Computational Experiments

In this section, we discuss the estimation of basic parameters of the model, and then present an application of the proposed methodology to determine the intermodal terminals that should be closed to hazmat freights. Finally we analyze the solution and provide managerial insights.

Here we continue to employ the intermodal service chain of Norfolk Southern in US, including 19 intermodal terminals and 31 types of intermodal train services differentiated by route and intermediate stops. These train services connect 37 pairs of shipper/receivers distributed in different parts of US. There are two types of train services, regular and priority, where the latter train type is 25% faster than the former one. To ensure each shipment using both the road and rail, the generated demand data does not include the shipper and receiver with access to the same terminal. We also consider the delivery time of 42 hours for each shipment (discussions about the delivery time can be found in the previous chapter). The estimation of other parameters, such as drayage fuel charge, average drayage speed, regular and priority intermodal rail-haul costs and fixed costs, and the risk parameters, follows the previous chapter as well. The solution methodology was coded in C# and numerical experiments were performed on Intel Core i5 CPU 1.80 GHz with 8 GB ram. The recorded CPU time for this experiment is approximately 135 minutes with 500 iterations.

4.3.4.1. Solution and Discussion

We ran the algorithm multiple times, and the best solution was the same each time. The best solution indicates that three terminals, including New York, Chicago and Detroit, should be closed to hazmat containers. The resulting total cost is $19,169,010, while 11,415,670 people are exposed to risk. Tables 4-1 and 4-2 provide the cost and risks for the non-regulated and INDA solutions, respectively. The non-regulated case is the one in which the government does not interfere on the use of the network by hazmat vehicles, and the carrier is the only decision maker. Thus, the lower level problem is regarded as the non-regulated model. As we see, government can reduce the total population exposure for 1,668,415 people and even carrier’s total cost for $8,543 by regulating hazmat shipments, and hence, both sides are better off with the network design policy. Please note that, the reduction in the carrier’s total cost after regulating the network is due to consideration of new inbound and outbound drayage segments. It was also noticed that, closing New York and Chicago terminals forces the relevant traffic transited through

Philadelphia and Indianapolis respectively. The traffic of Detroit was transited through both Indianapolis and Fort Wayne.

Table 4-1: Non-regulated

Cost = $19,177,553		Risk = 13,084,085 people	
Rail-haul	Drayage	Rail-haul	Drayage
3,706,015	15,471,538	2,748,027	10,336,058

Table 4-2: INDA

Cost = $19,169,010		Risk = 11,415,670 people		New segments = 5,127 miles	
Rail-haul	Drayage	Rail-haul	Drayage	Inbound	Outbound
3,472,310	15,696,700	2,540,800	8,874,870	3,038	2,089

Table 4-3 provides the relevant details on the 31 intermodal train services, where the maximum length for each train is 120 containers. For example, the first row refers to the intermodal train service that originates in Atlanta and terminates in Detroit, and has one stop in Knoxville. A total of one regular train is needed to move the specified containers, which would incur a fixed train cost of $21,243 and expose 4,896 people. Please note that, Detroit is closed to hazmat containers, so the second leg of the service (Knoxville to Detroit) could not be used, and only the first leg (Atlanta to Knoxville) is utilized.

According to Table 4-3, eight trains are not used. It was noticed that, the relevant traffic transited through three services of Jacksonville-Chicago, Atlanta-Philadelphia and Memphis-Philadelphia. Finally, Philadelphia, Charlotte and Indianapolis are 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. In addition, Philadelphia and Indianapolis handle additional traffic due to the closure of New York, Chicago and Detroit terminals.

To preserve the connectivity of the network after closing the terminals, respectively 3,038 and 2,089 miles of inbound and outbound drayage segments need to be constructed. While the intermodal network requires 5,127 miles of additional drayage to be built, 6,284 miles of inbound and outbound drayage are never used due to the terminal closure. Tables 4-4 and 4-5 present the list of the new drayage segments selected to be added to the network. The cost of building drayage segments varies considerably according to degree of urbanization, roadway width, number of lanes, etc. According to the Florida Department of Transportation (FDT, 2013), construction cost of a new 2-lane undivided road is $2,196,229 per mile in rural areas. Therefore, the total construction cost of drayage segments for INDA is approximately $11 billion.

Table 4-3: Attributes of intermodal trains

From	To	Stop	Regular	Priority	Train Cost	Risk
Atlanta	Detroit	1	1	0	21,243	4,896
Atlanta	New York	1	0	0	0	0
Atlanta	Philadelphia	2	9	0	710,749	583,926
Charlotte	New York	1	3	0	179,428	155,344
Charlotte	Chicago	1	2	0	139,071	63,840
Charlotte	Detroit	1	0	0	0	0
Chicago	Philadelphia	1	0	0	0	0
Chicago	New York	0	0	0	0	0
Chicago	Charlotte	2	3	0	207,298	172,440
Chicago	Jacksonville	2	1	0	74,683	36,838
Cincinnati	Jacksonville	3	1	0	65,691	17,144
Columbus	Norfolk	1	2	0	114,263	70,840
Detroit	Philadelphia	2	1	0	56,046	53,520
Detroit	New York	1	0	0	0	0
Indianapolis	Philadelphia	2	3	0	186,439	151,508
Indianapolis	New York	1	1	0	47,542	38,400
Indianapolis	Atlanta	0	2	0	115,594	55,952
Jacksonville	Chicago	2	3	0	233,926	103,800
Jacksonville	Philadelphia	1	1	0	96,144	69,550
Memphis	Philadelphia	2	1	0	118,334	38,580
New York	Chicago	2	1	0	33,299	31,978
New York	Detroit	1	0	0	0	0
New York	Indianapolis	2	1	0	47,406	64,737
New York	Charlotte	1	3	0	118,478	141,050
New York	Atlanta	2	0	0	0	0
Philadelphia	Chicago	2	2	0	158,599	145,712
Philadelphia	Detroit	2	1	0	50,236	21,990
Philadelphia	Indianapolis	2	1	0	88,288	65,880
Philadelphia	Atlanta	2	6	0	432,079	341,780
Philadelphia	Jacksonville	1	3	0	177,474	111,095
Philadelphia	Memphis	1	0	0	0	0
Intermodal terminals		Regular	52			
		Priority		0		
		Fixed cost			**722,997**	
		Risk				**2,540,800**
Container routing					**2,749,313**	
Total			**52**	**2**	**3,472,310**	

Table 4-4: New inbound drayage segments

Shipper	Source terminal	Distance (miles)
Richmond	Columbus	210
Annapolis	Richmond	136
Battle Creek	Cincinnati	283
Battle Creek	Indianapolis	220
Battle Creek	Columbus	242
Gadsden	Memphis	264
Fremont	Pittsburgh	24
Van Wert	Columbus	123
State College	Cleveland	238
State College	Philadelphia	193
York	Pittsburgh	214
York	Richmond	202
Hendersonville	Charlotte	104
Douglas	Atlanta	199
La Porte	Indianapolis	144
Muncie	Cincinnati	107
Muncie	Columbus	135
Total		**3,038**

Table 4-5: New outbound drayage segments

Destination terminal	Receiver	Distance (miles)
Indianapolis	La Porte	144
Richmond	Annapolis	136
Pittsburgh	Fremont	24
Cleveland	Battle Creek	241
Fort Wayne	Xenia	143
Indianapolis	Battle Creek	220
Indianapolis	Xenia	134
Columbus	Battle Creek	242
Indianapolis	Fremont	237
Charlotte	Hendersonville	104
Cincinnati	Muncie	107
Fort Wayne	La Porte	101
Cincinnati	La Porte	256
Total		**2,089**

Different from the single mode road networks, where the government is the only stakeholder, the rail-truck intermodal networks have other important stakeholders (i.e., private carrier companies) which need to be coordinated with the government when adopting regulating policies. Although the network design policy could be an applicable approach to mitigate the risk in a road network, it does not seem to be an attractive choice to the private sector involved in an intermodal network due to the rigid government's restrictions. Hence, we propose a more flexible policy that employs tolls at certain terminals in the next section.

4.4. Bi-objective Toll-setting Policy (BOTP)

Toll-setting policy discourages carriers from using certain intermodal terminals by assigning tolls to those terminals. As we mentioned in the literature review section, Marcotte et al. (2009) were the first who applied a bi-level toll policy to hazmat transportation. Assuming both hazmat traffic and regular traffic affect population safety, Wang et al. (2012) suggested a dual toll setting model to mitigate the risk. They formulated a two-stage model in which the first stage problem was solved by the branch and bound and the null space active set method, and the second stage problem was solved using linear programming techniques. Different from these studies, we impose tolls on facilities, rather than the links; while similar to their approach, at the upper level of the toll setting problem, the government sets tolls such that total transportation risk is minimized. To find a set of minimum tolls, we consider minimization of toll costs besides the transportation risk as the objective functions (equations 4-16 and 4-17). In other words, although the government's main concern is to minimize the population exposure, they also take the toll costs imposed on carriers into account to make the policy more attractive and assure its successful execution.

4.4.1. Model Formulation

Let $toll_j$ and $toll_k$ represent the tolls for origin terminal j and destination terminal k respectively. Based on the previously introduced notation, we formulation BOTP as follows.

$$\min_{toll_j, toll_k} \sum_{z \in Z_{il}} \sum_{p \in P_{ij}} E^p X_z^p + \sum_{z \in Z_{il}} \sum_{q \in Q_{kl}} E^q X_z^q + \sum_{z \in Z_{il}} \sum_{v \in V_{jk}} E^v X_z^v \tag{4-16}$$

$$\min_{toll_j, toll_k} \sum_{j \in J} toll_j \sum_{z \in Z_{il}} \sum_{p \in P_{ij}} X_z^p + \sum_{k \in K} toll_k \sum_{z \in Z_{il}} \sum_{q \in Q_{kl}} X_z^q \tag{4-17}$$

where X_z^p, X_z^q and X_z^v solve:

$$\begin{aligned} \min \sum_{z \in Z_{il}} \sum_{p \in P_{ij}} C^p X_z^p + \sum_{z \in Z_{il}} \sum_{q \in Q_{kl}} C^q X_z^q + \sum_{z \in Z_{il}} \sum_{v \in V_{jk}} C^v X_z^v + \sum_{v \in V_{jk}} FC^v N^v \\ + \sum_{j \in J} toll_j \sum_{z \in Z_{il}} \sum_{p \in P_{ij}} X_z^p + \sum_{k \in K} toll_k \sum_{z \in Z_{il}} \sum_{q \in Q_{kl}} X_z^q \end{aligned} \tag{4-18}$$

s.t.

$$\sum_{p \in P_{ij}} X_z^p = \sum_{v \in V_{jk}} X_z^v, j \in J, z \in Z_{il} \tag{4-19.a}$$

$$\sum_{v \in V_{jk}} X_z^v = \sum_{q \in Q_{kl}} X_z^q, k \in K, z \in Z_{il} \tag{4-19.b}$$

$$\sum_{q \in Q_{kl}} X_z^q = D_z, z \in Z_{il} \tag{4-20}$$

$$\sum_{z \in Z_{il}} X_z^v \leq U^v N^v, v \in S_{jk}^v \cap V_{jk} \tag{4-21}$$

$$Oh_j \geq X_z^v, v \in V_{jk}, z \in Z_{il} \tag{4-22.a}$$

$$Oh_k \geq X_z^v, v \in V_{jk}, z \in Z_{il} \tag{4-22.b}$$

$$OY_z^p \geq X_z^p, p \in P_{ij}, z \in Z_{il} \tag{4-23.a}$$

$$OY_z^v \geq X_z^v, v \in V_{jk}, z \in Z_{il} \tag{4-23.b}$$

$$OY_z^q \geq X_z^q, q \in Q_{kl}, z \in Z_{il} \tag{4-23.c}$$

$$t^p Y_z^p + t^v Y_z^v + t^q Y_z^q \leq DT_z, p \in P_{ij}, q \in Q_{kl}, v \in V_{jk}, z \in Z_{il}, j \in J \tag{4-24}$$

$$X_z^p, X_z^v, X_z^q, N^v \geq 0, \tag{4-25}$$

$$Y_z^p, Y_z^v, Y_z^q \in \{0,1\}$$

$$0 \leq toll_j, toll_k \leq 1000$$

As shown, the lower level problem is the same as the network design problem except that it has two extra terms related to the toll costs in the objective function. Also, we set the maximum value of tolls to \$1000. Further discussions about this value are provided in Section 4.5. To solve the developed bi-objective bi-level model, we use the speed-constrained multi-objective PSO (SMPSO) (Nebro et al., 2009) since it obtains remarkable results in terms of both, accuracy and speed. Section 4.4.1 discusses the developed SMPSO in detail.

4.4.2. SMPSO

SMPSO starts with creating the initial population and setting the positions and the velocities of the particles with random values. For the toll setting problem we use a real coding. Each particle consists of upper level's decision variables which represent the tolls assigned to each intermodal terminal (see Figure 4-4). After initializing the population, an archive of leaders is formed consisting of non-dominated solutions (the archive size is set to 20 in this research). Then, similar to the single objective PSO, the main loop of the algorithm starts (see Figure 4-5). First, the positions and the velocities of the particles are updated and a polynomial mutation is applied. Then, solving the lower level problem using ILOG CPLEX, the fitness functions are evaluated, and *pbest*s, *gbest* and the leader's archive are updated subsequently. To choose the particles for the leader's archive, the crowding distance of NSGA-II (Deb et al., 2002) is used (for more details on NSGA-II, please see Section 3.5.2). Application of both mutation and crowding distance operators preserves the diversity of non-dominated solutions in the archive of leaders.

Origin terminals				Destination terminals			
$toll_1$	$toll_2$	…	$toll_b$	$toll_1$	$toll_2$	…	$toll_e$

Figure 4-4: Individual representation

4.4.2.1. Polynomial Mutation

Polynomial mutation was first proposed by Deb and Goyal (2006). Applying this operator the new particle $p\acute{o}s_{r,s}$ is generated as follows:

$$p\acute{o}s_{r,s} = pos_{r,s} + \delta_s(pos_s^u - pos_s^l) \quad (4\text{-}26)$$

$$\delta_s = \begin{cases} [2rand_s + (1-2rand_s)(1-\delta_1)^{\eta+1}]^{1/(\eta+1)} - 1, if\ rand_s < 0.5 \\ 1 - [2(1-rand_s) + 2(rand_s - 0.5)(1-\delta_1)^{\eta+1}]^{1/(\eta+1)}, if\ rand_s \geq 0.5 \end{cases} \quad (4\text{-}27)$$

$$\delta_1 = \frac{pos_{r,s} - pos_s^l}{pos_s^u - pos_s^l}, \delta_2 = \frac{pos_s^u - pos_{r,s}}{pos_s^u - pos_s^l}, rand_s \in U[0,1] \quad (4\text{-}28)$$

where pos_s^u and pos_s^l are the upper and lower limit values, and η is the mutation index which is set to 20.

Initialize swarm

Initialize leader's archive

while iteration < maxIteration

    Update velocity of particle *r*

    Update position of particle *r*

    Apply polynomial mutation

    Evaluate the fitness function using CPLEX

    Update leader's archive

    Update *pbest* and *gbest*

end while

Return leader's archive

Figure 4-5: Pseudocode of the developed SMPSO

4.4.2.2. Crowding Distance Operator

The crowding distance value of a solution provides an estimate of the density of solutions surrounding that solution (Deb et al., 2002). The crowding distance of solution *i* is equal to the size of the largest rectangle containing *i* but not any other solution (see Figure 4-6).

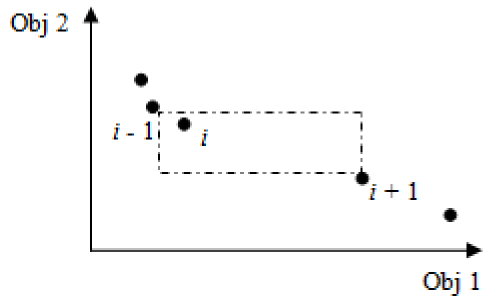


Figure 4-6: Crowding distance calculation (Adopted from Deb et al. (2002))

To calculate the crowding distance, the following procedure is repeated for each objective function. First the solutions are sorted ascendingly based on their objective function values. Then, the crowding distance of each solution, which is the average distance of its nearby solutions, is estimated. The total crowding distance value of a solution is the sum of the crowding distances of this solution for both objective functions.

4.4.3. Solution and Discussion

Table 4-6 and Figure 4-7 present a Pareto frontier with solution *A* and *Q* constituting the two extremes. *A* is the least risky solution, with the total toll value of $1,047,107 and total risk of exposing 11,898,610 individuals. On the other hand, *Q* has the lowest toll cost of zero, which is compensated by the total risk of approximately 13 million individuals. With regard to Figure 4-7, it is easy to see that risk reductions entails larger toll costs when moving from *A* to *O*, whereas it is achieved at small cost for the rest of the solutions. Moving from *O* to *Q* decreases the exposure for approximately 869,167 people, while increases the toll cost for nearly $8,181, which means that the cost of exposing one fewer individual is $0.009.

Mitigating the exposure risk is the key concern of the government, therefore our study emphasizes on the min risk solution (solution *A*). To have a better understanding of this solution, the corresponding breakdown information is provided in Table 4-8. The specified demand can be met by spending around $19.8 million, and exposing approximately 11.8 million individuals.

Table 4-6: Alternative optimal solutions

	Risk (people)	Toll cost ($)
A	11,898,610	1,047,107
B	11,926,720	963,685
C	11,940,028	695,466
D	11,947,109	521,117
E	11,950,035	515,530
F	11,950,941	376,892
G	11,963,005	296,895
H	11,969,207	204,729
I	12,015,443	195,953
J	12,019,545	108,975
K	12,065,485	74,765
L	12,081,450	35,814
M	12,100,251	22,609
N	12,145,332	15,135
O	12,214,918	8,181
P	13,069,061	2,615
Q	13,084,085	0

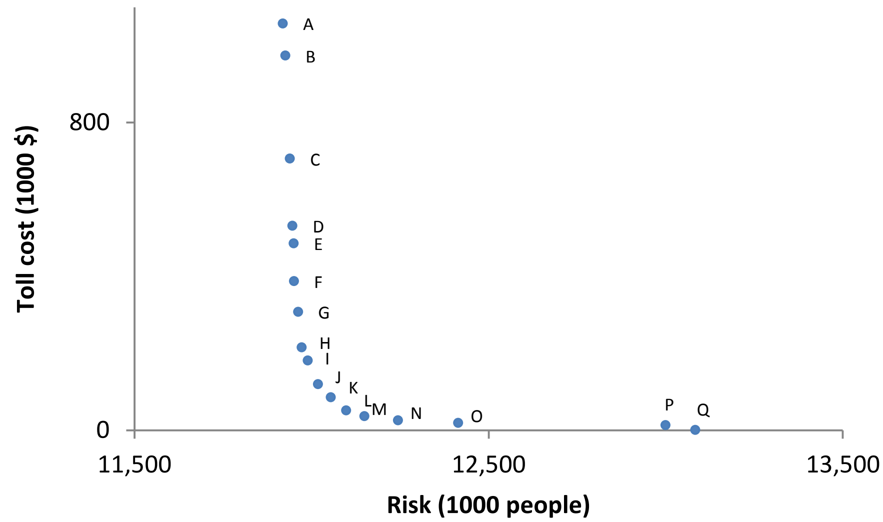


Figure 4-7: Pareto frontier

Table 4-7: Solution A

Cost = $19,827,592			Risk = 11,898,610 people	
Rail-haul	Drayage	Toll	Rail-haul	Drayage
3,743,202	15,510,312	1,047,107	2,654,156	9,244,454

The optimal set of tolls is presented in Table 4-8. As shown, New York, Charlotte and Indianapolis have the highest tolls, while Philadelphia, Knoxville, Cincinnati and Fort Wayne are toll free. Please note that, even though the Philadelphia terminal is located at a highly populated area, it is still toll free. This is because our model minimizes the overall system risk by assigning tolls, rather than focusing on each single terminal.

Table 4-8: Tolls for intermodal terminals

Terminal	Toll ($)	Terminal	Toll ($)
New York	976.88	Memphis	141.52
Philadelphia	0	Cincinnati	0
Richmond	5.65	Indianapolis	188.78
Norfolk	59.53	Columbus	18.57
Roanoke	153.94	Fort Wayne	0
Charlotte	227.61	Chicago	106.11
Knoxville	0	Detroit	119.84
Atlanta	94.50	Cleveland	72.89
Macon	6.08	Pittsburgh	1.28
Jacksonville	1.40		

Table 4-9 provides the relevant details on the intermodal train services. Notice that six trains with origin or destination in New York, one train with origin in Indianapolis and another train with destination in Memphis are not used. The relevant traffic transited through Philadelphia, Cincinnati and Knoxville respectively. Finally, Philadelphia and Atlanta are the busiest terminals, which in turn can be explained by the fact that nine of the 31 train services originate at these yards and another eleven transit them. In addition, Philadelphia handles additional traffic due to high toll of New York.

Table 4-9: Attributes of intermodal trains

From	To	Stops	Regular	Priority	Train Cost	Risk
Atlanta	Detroit	1	2	0	93,466	46,391
Atlanta	New York	1	1	0	15,557	20,125
Atlanta	Philadelphia	2	9	0	622,632	628,488
Charlotte	Chicago	1	2	0	109,900	121,144
Charlotte	Detroit	1	2	0	117,609	66,934
Charlotte	New York	0	0	0	0	0
Chicago	Charlotte	2	3	0	174,572	178,619
Chicago	Jacksonville	2	2	1	182,110	109,804
Chicago	New York	0	0	0	0	0
Chicago	Philadelphia	1	1	0	61,894	76,111
Cincinnati	Jacksonville	3	2	0	92,369	30,432
Columbus	Norfolk	1	2	0	94,308	71,951
Detroit	New York	1	0	0	0	0
Detroit	Philadelphia	2	1	0	60,480	71,340
Indianapolis	Atlanta	0	0	0	0	0
Indianapolis	New York	1	0	0	0	0
Indianapolis	Philadelphia	2	3	0	117,409	117,748
Jacksonville	Chicago	2	2	1	194,474	105,451
Jacksonville	Philadelphia	1	1	0	81,270	69,550
Memphis	Philadelphia	2	1	0	105,546	41,306
New York	Atlanta	2	0	0	0	0
New York	Charlotte	1	2	0	54,101	99,386
New York	Chicago	2	1	0	20,325	34,378
New York	Detroit	1	0	0	0	0
New York	Indianapolis	2	1	0	28,998	54,875
Philadelphia	Atlanta	2	7	0	358,072	349,874
Philadelphia	Chicago	2	2	0	150,679	168,442
Philadelphia	Detroit	2	1	0	44,404	27,697
Philadelphia	Indianapolis	2	1	0	61,581	54,039
Philadelphia	Jacksonville	1	3	0	131,262	110,395
Philadelphia	Memphis	1	0	0	0	0
Intermodal terminals		Regular	52			
		Priority		2		
		Fixed cost			**770,186**	
		Risk				**2,654,480**
Container routing					**2,973,016**	
Total			**52**	**2**	**3,743,202**	

4.4.4. Managerial Insights

4.4.4.1. Variation in Maximum Toll Cost

As we mentioned in the BOTP formulation, we restrict the maximum toll costs to $1000. To examine the effect of changing the maximum toll cost on the min risk solutions, we further considered two additional cases: maximum toll = $500 (Case 1) and maximum toll = $1500 (Case 2). Table 4-10 lists the tolls for relevant intermodal terminals. Not only the toll amounts varies from case to case, but also the share of terminals changes. In Case 1, New York, Detroit and Roanoke have the highest tolls, while in Case 2, New York, Atlanta and Norfolk have the highest tolls.

Table 4-10: Tolls for intermodal terminals

Terminal	Max toll $500	Max toll $1000	Max toll $1500	Terminal	Max toll $500	Max toll $1000	Max toll $1500
New York	464.54	976.88	1371.08	Memphis	324.00	141.52	33.10
Philadelphia	15.960	0	0.23	Cincinnati	259.49	0	102.68
Richmond	29.34	5.65	179.20	Indianapolis	379.04	188.78	307.02
Norfolk	58.28	59.53	1076.64	Columbus	111.01	18.57	45.00
Roanoke	384.59	153.94	0.11	Fort Wayne	25.45	0	0.10
Charlotte	340.55	227.61	0	Chicago	54.33	106.11	225.53
Knoxville	2.26	0	50.41	Detroit	445.79	119.84	1.47
Atlanta	20.86	94.50	1083.64	Cleveland	374.41	72.89	166.05
Macon	0.13	6.08	16.14	Pittsburgh	143.63	1.28	326.68
Jacksonville	242.45	1.40	481.57				

Table 4-11 compares the min risk solutions for the three cases. When we decrease the maximum toll cost, total risk increases to 11,988,818 people. On the other hand, increasing the maximum toll cost would decrease the total risk to 11,847,953 people, but increase the carrier's total costs to $22,864,751. We have also experimented with several amounts greater than $1500, but saw no improvement in the overall result. With regard to minor variation in the total risk value, we can conclude that the base solution (maximum toll = $1000) is rather robust to minor variations in maximum toll amount.

Table 4-11: Impact of maximum toll cost

Max toll cost ($)	Cost ($)			Risk (people)	
	Rail-haul	Drayage	Toll	Rail-haul	Drayage
500	3,812,949	15,552,045	1,798,767	2,736,872	9,251,946
1000	3,743,202	15,510,312	1,047,107	2,654,156	9,244,454
1500	3,826,401	15,521,100	3,517,250	2,667,846	9,180,107

4.4.4.2. Network Design vs. Toll Setting

Table 4-12 gathers the information for the three cases of non-regulated, BOTP (min risk solution) and INDA. Based on this table, INDA exposes fewer individuals than the min risk solution achieved by BOTP. Both BOTP and INDA incur fewer exposures than the non-regulated case. Comparing INDA and BOTP, we see that the former leads to a lower transportation risk, and in return charges the government to construct 5,127 miles of new drayage segments to avoid infeasibility. In addition, applying strictly the INDA policy, a part of the infrastructure, including closed intermodal terminals and their connected rail and road segments, would be underutilized. On the other hand, despite the higher risk, BOTP benefits the government by over 1 million dollars, which can be used to help recuperate the cost of road construction and maintenance. Furthermore, applying INDA, New York, Chicago and Detroit are closed; while under BOTP, a different set of terminals, i.e. New York, Charlotte and Indianapolis, have the highest tolls. This difference can be justified by the fact that, due to closure of a number of terminals and addition of a set of inbound and outbound drayage segments in INDA, the networks of the two policies are different.

The government could consider using the two policies as a two-stage plan, with BOTP at the first stage and INDA at the second. In the first stage, and with the tolls income, the government can extend the network by constructing additional drayage segments. Then, through the second stage, the carriers are suggested to close certain terminals, only to the hazmat transportation. Given extra road connections and lower transportation costs of INDA, the scenario could be attractive to the carrier, and thus be implemented.

Table 4-12: Three scenarios

	Cost ($)		Risk (people)		
	Rail-haul	Drayage	Rail-haul	Drayage	
Non-regulated	3,706,015	15,471,538	2,748,027	10,336,058	
BOTP	3,743,202	15,510,312	1,047,108	2,654,480	Toll costs: $1,047,107
INDA	3,472,310	15,696,700	2,540,800	8,874,870	New segments = 5,127 miles

4.5. Conclusion

This study suggests two bi-level models for regulating a rail-truck intermodal network of hazmat. The models consider government and carrier at two levels of administration, and formulate their interaction to regulate the shipment of hazardous materials. For the intermodal network design model, at the higher level, the government aims to select the intermodal terminals to close such that the total transportation risk is minimized; while, at the lower level, the carrier makes routing decisions and thus determines the transportation risk. Based on this formulation, a PSO algorithm was proposed for solving realistic problem instances.

As an improved policy to INDA, we further developed a toll setting approach and formulated a bi-objective bi-level model to regulate the use of intermodal terminals for hazmat. In the new model, the government determines the tolls to discourage the carrier from using certain terminals. The model is then solved by a multi-objective PSO, and a set of non-dominated solutions are approximated. Comparing the min risk solution achieved by the toll setting policy and the one achieved by the network design policy shows that INDA can find better solution in terms of transportation risk, however incurs the government construct 5,127 miles of new drayage segments, which would cost approximately $11 billion.

This work contributes to the literature by following aspects. First of all, unlike all the studies in this area that focus exclusively on single mode, we consider a rail-truck intermodal network which is completely different from the single-mode network in terms of infrastructure and operations done. Secondly, unlike most of the approaches in the literature that seem to concentrate only on one aspect, we focus on the combined location and routing model development. Furthermore, two bi-level mixed-integer program reformulations of the proposed policies are provided, and accordingly, two hybrid solution procedures based on the PSO algorithm is proposed for real size problems. Finally, the chapter compares the two proposed regulating policies, i.e. network design and toll setting policies, and discusses the advantages and disadvantages of each. For the future research, beside the transportation risk we will consider the total risk during the transfer process at intermodal terminals. Additionally, it would be interesting to incorporate risk equity into the proposed model to further enhance its applicability.

5. Conclusion and Future Research

5.1. Conclusion

In contrast to many other application domains, the use of operations research models and methods for intermodal transportation is still a very young area. In this dissertation, we proposed a set of three compatible approaches towards operational, tactical and strategic planning of intermodal transportation.

In Chapter 2 and at the operational level, we considered a container port terminal and proposed an analytical approach to schedule the cranes, such that the unloading of inbound vessels and the loading of outbound vehicles could be completed in minimum time. Since the problem is NP-hard, a genetic algorithm (GA) equipped with a novel decoding procedure was proposed. This method was tested on problem sets generated using the realistic parameters from the Port of Montreal and the Port of Singapore and results were compared with another meta-heuristic technique (Elitist Evolutionary Strategy). The key features of this framework are the formulation of the problem as a multi-processor two-stage model, the consideration of the availability time windows for cranes and the solution procedure applied.

Our computational experiments showed that the distribution of unavailability times has a direct bearing on the completion time. This implies that the unavailable time windows could be arranged so as to ensure smooth flow of jobs without changing the actual unavailability duration. Also, according to the results, the proposed GA outperforms the other two techniques in most instances, and within a reasonable amount of computing time.

In Chapter 3, we studied the tactical level problem of capacity planning and routing of regular and hazardous goods in a rail-truck intermodal network when the demand for transportation is uncertain, and therefore, congestion may arise at the intermodal terminals. The problem was solved using an iterative solution procedure incorporating a heuristic and a multi-objective genetic algorithm to generate a model that could be solved by CPLEX. The application of the model was illustrated using a real problem instance based on the intermodal service chain of Norfolk Southern in the US. The key features of this framework are incorporating uncertainty resulting from the uncertain nature of the hazmat transportation problems, considering the congestion at intermodal terminals as a source of exposure in hazmat transportation problem and combining capacity planning with the routing of hazardous materials in the congested networks.

Our computational experiments showed that besides the drayage and rail-haul, congestion at intermodal terminals is a main source of population exposure. Improving the service time at busy terminals using more or faster handling equipment (e.g. cranes) and applying tighter routing regulations, or even closing the rail/road segments that pass through populated centers, can considerably mitigate the potential risk. Finally, since the delivery time is a major concern for many companies, it is important to consider the impact of congestion (or capacity) of intermodal terminals on the supply (delivery) time.

In Chapter 4, we studied the strategic level problem of regulating intermodal transportation of hazardous materials. This chapter aimed to assist the government in regulating the usage of intermodal terminals for hazardous material transportation using the bi-level programming approach. A bi-level network design model (INDA) and a bi-level bi-objective toll-setting policy model (BOTP) were proposed to mitigate the transportation risk. We developed two hybrid particle swarm optimizations that integrate CPLEX optimization to solve the models. The application of our models was illustrated by a real problem instance based on the intermodal service chain of Norfolk Southern in the US. The key features of this framework are the consideration of a rail-truck intermodal network, the combination of location and routing model development, the reformulation of two bi-level mixed-integer program for the proposed policies, and accordingly, the development of two hybrid solution procedures based on the PSO algorithm for real size problems.

Based on our computational experiments, the government could use the two policies as a two-stage plan, with BOTP at the first stage and INDA at the second. In the first stage, and with the toll income, the government could extend the network by constructing additional drayage segments. Then, through the second stage, the carriers were suggested to close certain terminals, only to the hazmat transportation. Given extra road connections and lower transportation costs of INDA, the scenario could be attractive to the carrier, and thus be implemented.

5.2. Future Directions

Specific extensions related to each of the three contributions were elaborated in the respective chapters i.e. Chapters 2-4. In the following, we point out other directions for the future research.

5.2.1. Time-dependent Stochastic Network

Routing of hazmat shipments in the networks that have time-dependent stochastic attributes (such as travel times) is an interesting and challenging operations research problem that has not yet been studied adequately. The results from fixed travel time models may produce schedules which lead to longer journeys, and hence give rise to further congestion and associated costs. Hence, in situations where travel times are uncertain and the probability distributions vary with the time of day, the transport network should be modeled as a stochastic time-dependent network. In such a network, the link attributes (such as travel times, incident probabilities, and population exposure) are represented as random variables with a priori probability distributions that vary with time (Erkut et al., 2007).

In deterministic networks, there is only one minimum time path connecting a shipper to a receiver. However, in stochastic time-dependent networks, multiple paths may have positive probability of having the least time, as the arc times are stochastic. Therefore, a set of non-dominated solutions can be estimated. The major concern to solve the routing problems in stochastic time-dependent networks is the collection and processing of the data required to assess the probability distribution used as input to the model. Time-dependent stochastic networks have been studied during the past two decades, but only very few of them consider hazmat transportation (e.g., Bowler and Mahmassani, 1998; Miller-Hooks and Mahmassani, 1998). Among these few papers, none of them take multiple objectives or multiple modes into account. In addition, they are all about local route planning, rather than global routing. Unlike the local routing, which focuses on a single commodity and a single origin-destination route plan, the global routing problem involves multi-commodity and multiple origin-destination routing decisions. In the future, we can study the global routing of hazmat freights in a time-dependent stochastic network.

5.2.2. Terrorist Attack

Another future research direction is to consider the potential for a terrorist attack on a hazmat vehicle. Traditionally, traffic accidents or human error were regarded as factors affecting risk. However, the hazmat vehicles could be the desirable targets for terrorists, specifically because of the corresponding exposure risks. This fact should be considered when modeling the risk in the problems similar to ours in Chapters 3 and 4. To assess the risk of terrorist attack involving hazardous materials, the tiered approach used to designate varying levels of highway/rail security-sensitive materials[2], frequency of shipment of hazmat freights and the consequence of attack should be considered (Reniers and Zamparini, 2012).

[2] Security-sensitive materials have legitimate industrial use but can be exploited by terrorists and be weaponised (e.g. certain explosive materials and ammonium nitrate).

In addition to the risk assessment, the routing of hazmat freight could be affected by probability of terrorist attack. Besides the minimization of cost, minimizing the probability of a successful terrorist attack could also be regarded as objective functions. Applying game theory to model the interaction between a carrier and a terrorist would help the carrier make decisions of which routes to use with what frequencies with regard to threat of the terrorism. Reilly et al. (2012) is one of the few studies which model the possible role of a terrorist when designing a network of hazmat. They developed a Stackelberg game in which the government acts as a leader to maximize the carriers' payoff and limit the terrorist's payoff by restricting specific facilities. The main drawback of the developed model is that only one carrier is considered. The model can be extended to address multiple carriers, each with several origins and destinations. Furthermore, it would be interesting to study a similar problem in an intermodal network with multiple stakeholders. Unlike the road network, where the government has the options of restricting specific facilities or closing the links, the rail-truck intermodal networks have other important stakeholders (i.e., private carrier companies) which are important to be coordinated with the government when making restricting decisions.

5.2.3. Risk Equity

Finally, equity in distribution of risk should be taken into account when designing hazmat management strategies acceptable to the public. Since carriers' decisions are usually made without considering the general setting, it may happen that some parts of the transportation network are overloaded with hazmat freights. This may cause considerable increase of accident rates in those parts, resulting in inequity on distribution of the risk. In traditional approaches, different paths would be generated to alternate the route among them and hence distribute the risk. Recently, bi-level optimization is used to tackle risk equity. Since the government cannot impose specific routes on carriers, policies could be adopted to regulate the use of the network links and therefore promote equity in the spatial distribution of risk. Although several studies have focused on risk equity (e.g. List and Mirchandani, 1991; Current and Ratick, 1995; Kang et al., 2014), very few of them have presented a bi-level formulation (e.g. Bianco et al., 2009), which is a more appropriate methodology to study an uncooperative situation where different authorities act as multiple decision makers. All available models consider only one mode of transportation; however risk equity in an intermodal network is different from a single mode network. Different studies showed that equity can be enhanced using alternate routes for a shipment. Though this is possible in a road network, the scarcity of railroad in different areas does not present many routing options. In a rail network, train make-up, i.e., the composition of the train, is the major factor affecting the risk equity. For a certain amount of demand, the use of fewer trains would lead to an increase in the exposure zone while reducing the number of times people close to the tracks are exposed. Verma and Verter (2007) showed that, when the train passes through a populated area, with a uniform population density, the exposure will spread over large number of people, and hence improve the equity. Studying the risk equity in a rail truck network of hazmat would be a significant contribution.

6. References

[1] AAR, 2006. Current rail hazmat conditions called "Untenable", https://www.aar.org/ViewContent.asp?Content_ID=3763 (Accessed April 18, 2014).

[2] AAR, 2012. Hazardous Materials Transportation. Association of American Railroads – Policy and Economics Department. August 2012.

[3] Abkowitz, M., Lepofsky, M. and Cheng, P. (1992). Selecting criteria for designating hazardous materials highway routes. Transportation Research Record, 1333, 30–35.

[4] Alicke, K. (2005). Modeling and optimization of the intermodal terminal Mega Hub. Container Terminals and Automated Transport Systems, 307-323.

[5] Al-Khayyal, F. A., and Falk, J. E. (1983). Jointly constrained biconvex programming. Mathematics of Operations Research, 8: 273.

[6] Alp, E. (1995). Risk-based transportation planning practice overall methodology and a case example. INFOR, 33(1): 4–19.

[7] Alumur, S., and Kara, B. Y. (2007). A new model for the hazardous waste location-routing problem. Computers & Operations Research, 34(5), 1406-1423.

[8] Batta, R. and Chiu, S. S. (1988). Optimal obnoxious paths on a network: transportation of hazardous materials. Operations Research, 36(1): 84–92.

[9] Bektas, T., and Crainic, T. (2007). A brief overview of intermodal transportation. CIRRELT.

[10] Beyer, H. G. and Schwefel, H. P. (2002). Evolution strategies: a comprehensive introduction. Natural Computing, 1(1), 3-52.

[11] Bianco, L., Caramia, M., and Giordani, S. (2009). A bilevel flow model for hazmat transportation network design. Transportation Research Part C: Emerging Technologies, 17(2), 175-196.

[12] Bianco, L., Caramia, M., Giordani, S., and Piccialli, V. (2012). A game theory approach for regulating hazmat transportation. Tech. Rep. RR-21.12, Dipartimento di Ingegneria dell'Impresa, University of Rome "Tor Vergata", Italy.

[13] Bierwirth, C. and Meisel, F. (2009). A fast heuristic for quay crane scheduling with interference constraints. Journal of Scheduling, 12(4), 345-360.

[14] Bierwirth, C. and Meisel, F. (2010). A survey of berth allocation and quay crane scheduling problems in container terminals. European Journal of Operations Research, 202(3), 615-627.

[15] Bontekoning, Y. M., Macharis, C. and Trip, J. J. (2004). Is a new applied transportation research field emerging?—A review of intermodal rail–truck freight transport literature. Transportation Research Part A, 38 1–34.

[16] Bowler, L. A., and Mahmassani, H. S. (1998). Routing of radioactive shipments in networks with time-varying costs and curfews (No. ANRCP--1998-11). Amarillo National Resource Center for Plutonium, TX (United States).

[17] Candler, W., and Townsley, R. (1982). A linear two-level programming problem. Computers & Operations Research, 9(1), 59-76.

[18] Cappanera, P., Gallo, G. and Maffioli, F. (2004). Discrete facility location and routing of obnoxious activities. Discrete Applied Mathematics, 133: 3–28.

[19] Carlo, H. J., Vis, I. F. and Roodbergen, K. J. (2013). Seaside operations in container terminals: literature overview. trends, and research directions. Flexible Services and Manufacturing Journal, 1-39.

[20] CBC, 2013, http://www.cbc.ca/news/canada/montreal/search-resumes-in-lac-m%C3%A9gantic-for-5-still-missing-1.1357940 (Accessed April 18, 2014).

[21] Chen, L., Bostel, N., Dejax, P., Cai, J. and Xi, L. (2007). A tabu search algorithm for the integrated scheduling problem of container handling systems in a maritime terminal. European Journal of Operations Research, 181(1), 40–58.

[22] Chen, L. and Langevin, A. (2011). Multiple yard cranes scheduling for loading operations in a container terminal. Engineering Optimization, 43(11), 1205-1221.

[23] Chen, F. and Lee, C. (2009). Minimizing the makespan in a two-machine cross-docking flow shop problem. European Journal of Operations Research, 193(1), 59–72.

[24] Chen, F. and Song, K. (2009). Minimizing makespan in two-stage hybrid cross docking scheduling problem. Computers & Operations Research, 36(6), 2066-2073.

[25] Chen, C., Vempati, V. and Aljaber, N. (1995). An application of genetic algorithms for flow shop problems. European Journal of Operations Research, 80(2), 389-396.

[26] Christiansen, M., Fagerholt, K., Nygreen, B., and Ronen, D. (2006). Maritime transportation. Transportation, 14, 189-284.

[27] Chung, S. H. and Choy, K. L. (2012). A modified genetic algorithm for quay crane scheduling operations. Expert Systems with Applications, 39(4), 4213-4221.

[28] CIY (2012). National Magazine Company, London. Available at: PSA Singapore. About Us: PSA Singapore. http://www.singaporepsa.com/aboutus.php (Accessed January 18, 2013).

[29] Colliers (2012). Available at: http://www.colliers.com/en-US/US/~/media/Files/MarketResearch/UnitedStates/Colliers_PortReport_2012q2_final.ashx?campaign=Colliers_Port_Analysis_NA_Aug-2012 (Accessed January 18, 2013).

[30] Corry, P. and Kozan, E. (2006). An assignment model for dynamic load planning of intermodal trains. Computers & Operations Research, 33: 1–17.

[31] Crainic, T. G., and Kim, K. H. (2007). Intermodal transportation. Transportation, 14, 467-537.

[32] Current, J., and Ratick, S. (1995). A model to assess risk, equity and efficiency in facility location and transportation of hazardous materials. Location Science, 3(3), 187-201.

[33] Daganzo, C. F. (1989). The crane scheduling problem. Transportation Research Part B: Methodological, 23(3), 159–175.

[34] De Jong, K. A. (1975). Analysis of the Behavior of a Class of Genetic Adaptive Systems (Doctoral dissertation), University of Michigan, Ann Arbor, MI.

[35] Deb, K. and Goyal, M. (1996). A combined genetic adaptive search (geneas) for engineering design. Computer Science and Informatics, 26(4), 30–45.

[36] Deb, K., Pratap, A., Agarwal, S. and Meyarivan, T. (2002). A fast and elitist multiobjective genetic algorithm: NSGA-II. IEEE Transactions on Evolutionary Computation, 6: 182–197.

[37] Elhedhli, S., and Hu, F. (2005). Hub-and-spoke network design with congestion. Computers and Operations Research, 32: 1615–1632.

[38] Elhedhli, S., and Wu, H. (2010). A Lagrangean heuristic for hub-and-spoke system design. INFORMS Journal on Computing, 22: 282–296.

[39] Erkut, E. and Gzara, F. (2008). Solving the hazmat transport network design problem. Computers and Operations Research, 35, 2234–2247.

[40] Erkut, E. and Verter, V. (1998). Modeling of transport risk for hazardous materials. Operations Research, 46(5): 625–642.

[41] Erkut, E., Tjandra, S. A., and Verter, V. (2007). Hazardous materials transportation. Handbooks in operations research and management science, 14, 539-621.

[42] Etiler, O., Toklu, B., Atak, M. and Wilson, J. (2004). A Genetic Algorithm for Flow Shop Scheduling. Journal of the Operational Research Society, 55(8), 830-835.

[43] Federal Railroad Administration, 2014. https://www.fra.dot.gov/Page/P0151 (Accessed April 18, 2014).

[44] Florida Department of Transportation, 2013. http://www.dot.state.fl.us/planning/policy/costs/costs-D3.pdf (Accessed April 18, 2014).

[45] Gambardella, L. M., Mastrolilli, M., Rizzoli, A. E., and Zaffalon, M. (2001). An optimization methodology for intermodal terminal management. Journal of Intelligent Manufacturing, 12(5-6): 521-534.

[46] Giannikos, I. (1998). A multiobjective programming model for locating treatment sites and routing hazardous wastes. European Journal of Operational Research, 104(2): 333–342.

[47] Gross, D. and Harris, C. M. (1998). Fundamentals of Queuing Theory**,** New York, Wiley.

[48] Guan, Y., Xiao, W. Q., Cheung, R. K. and Li, C. L. (2002). A Multiprocessor Task Scheduling Model for Berth Allocation: Heuristic and Worst-Case Analysis. Operations Research Letters, 30(5), 343–350.

[49] Gzara, F. (2013). A cutting plane approach for bilevel hazardous material transport network design. Operations Research Letters, 41(1), 40-46.

[50] Holland, J. H. (1975). Adaptation in Natural and Artificial Systems. University of Michigan Press, Ann Arbor.

[51] ILOG CPLEX 12.1 User's Manual, 2009 (ILOG Inc.).

[52] Jung, D. H., Park, Y. M., Lee, B. K., Kim, K. H. and Ryu, K. R. (2006). A quay crane scheduling method considering interference of yard cranes in container terminals. Advances in Artificial Intelligence, Springer Berlin Heidelberg, 461-471.

[53] Kang, Y., Batta, R., and Kwon, C. (2014). Generalized route planning model for hazardous material transportation with VaR and equity considerations. Computers & Operations Research, 43, 237-247.

[54] Kara, B. Y., Verter, V. (2004). Designing a road network for hazardous materials transportation. Transportation Science, 38(2), 188–196.

[55] Kaveshgar, N., Huynh, N. and Rahimian, S. K. (2012). An efficient genetic algorithm for solving the quay crane scheduling problem. Expert Systems with Applications, 39(18), 13108-13117.

[56] Kennedy, J. and Eberhart, R. (1995). Particle swarm optimization. In Proceedings of IEEE international conference on neural networks, 4(2), 1942-1948.

[57] Kim, K. Y. and Kim, K. H. (2003). Heuristic Algorithms for Routing Yard-Side Equipment for Minimizing Loading Times in Container Terminals. Naval Research Logistics (NRL), 50(5), 498-514.

[58] Lee, D. H., Wang, H. Q. and Miao, L. (2008a). Quay crane scheduling with noninterference constraints in port container terminals. Transportation Research Part E: Logistics and Transportation Review, 44(1), 124-135.

[59] Lee, D. H., Wang, H. Q. and Miao, L. (2008b). Quay crane scheduling with handling priority in port container terminals. Engineering Optimization, 40(2), 179-189.

[60] Legato, P., Trunfio, R. and Meisel, F. (2012). Modeling and solving rich quay crane scheduling problems. Computers & Operations Research, 39(9), 2063–2078.

[61] Li, W., Wu, Y., Petering, M., Goh, M. and Souza, R. (2009). Discrete time model and algorithms for container yard crane scheduling. European Journal of Operations Research, 198(1), 165-172.

[62] Liao, C. J., Tseng, C. T. and Luarn, P. (2007). A discrete version of particle swarm optimization for flowshop scheduling problems. Computers & Operations Research, 34(10), 3099-3111.

[63] List, G., and Mirchandani, P. (1991). An integrated network/planar multiobjective model for routing and siting for hazardous materials and wastes. Transportation Science, 25(2), 146-156.

[64] Marcotte, P., Mercier, A., Savard, G., and Verter, V. (2009). Toll policies for mitigating hazardous materials transport risk. Transportation science, 43(2), 228-243.

[65] Marinakis, Y. and Marinaki, M. (2008). A Bilevel Genetic Algorithm for a real life location routing problem. International Journal of Logistics Research and Applications: A Leading Journal of Supply Chain Management, 11(1), 49-65.

[66] Marinakis, Y., and Marinaki, M. (2013). A Bilevel Particle Swarm Optimization Algorithm for Supply Chain Management Problems. In Metaheuristics for Bi-level Optimization (pp. 69-93). Springer Berlin Heidelberg.

[67] Marianov, V. and Serra, D. (1998). Probabilistic maximal covering location-allocation for congested systems. Journal of Regional Science, 38(3): 401–424.

[68] Marianov, V. and Serra, D. (2001). Hierarchical location-allocation models for congested systems. European Journal of Operational Research, 135: 195–208.

[69] Marianov, V. and Serra, D. (2003). Location-allocation of multiple-server service centers with constrained queues or waiting times. Annals of Operations Research, 111: 35–50.

[70] Mathieu, R., Pittard, L., and Anandalingam, G. (1994). Genetic Algorithm Based Approach to Bi-level Linear Programming. Operations Research, 28(1), 1-21.

[71] Meisel, F. (2011). The quay crane scheduling problem with time windows. Naval Research Logistics (NRL), 58, 619-636.

[72] Miller-Hooks, E., and Mahmassani, H. S. (1998). Optimal routing of hazardous materials in stochastic, time-varying transportation networks. Transportation Research Record: Journal of the Transportation Research Board, 1645(1), 143-151.

[73] Mitchell, M. (1997). An Introduction to Genetic Algorithms. The MIT Press, Cambridge, Massachusetts.

[74] Nebro, A. J., Durillo, J. J., Garcia-Nieto, J., Coello Coello, C. A., Luna, F., and Alba, E. (2009). Smpso: A new PSO-based metaheuristic for multi-objective optimization. In Computational intelligence in miulti-criteria decision-making, 2009. mcdm'09. IEEE Symposium on. IEEE, 66-73.

[75] Nozick, L. K. and Morlok, R. K. (1997). A model for medium-term operations planning in an intermodal rail-truck service. Transportation Research Part A, 31(2): 91-107.

[76] Peterkofsky, R. I. and Daganzo, C. F. (1990). A branch and bound solution method for the crane scheduling problem. Transportation Research Part B: Methodological, 24(3), 159-172.

[77] PoM. Available at: http://www.port-montreal.com/en/index.html (Accessed January 22, 2013).

[78] Rajagopalan, S. and Yu, H. L. (2001). Capacity planning with congestion effects. European Journal of Operational Research, 134: 365–377.

[79] Rechenberg, I. (1973). Evolutions strategie: Optimierungtechnischer Systemenach Prinzipien der biologischen evolution. Stuttgart: Frommann-Holzboog.

[80] Reilly, A., Nozick, L., Xu, N., and Jones, D. (2012). Game theory-based identification of facility use restrictions for the movement of hazardous materials under terrorist threat. Transportation Research Part E: Logistics and Transportation Review, 48(1), 115-131.

[81] Reniers, G. L., and Zamparini, L. (Eds.). (2012). Security Aspects of Uni-and Multimodal Hazmat Transportation Systems. John Wiley & Sons.

[82] Revelle, C., Cohon, J. and Shobrys, D. (1991). Simultaneous siting and routing in the disposal of hazardous wastes. Transportation Science, 25: 138–145.

[83] Saccomanno, F. and Chan, A. (1985). Economic evaluation of routing strategies for hazardous road shipments. Transportation Research Record, 1020, 12–18.

[84] Samanlioglu, F. (2013). A multi-objective mathematical model for the industrial hazardous waste location-routing problem. European Journal of Operational Research, 226(2), 332-340.

[85] Stahlbock, R., and Voß, S. (2008). Operations research at container terminals: a literature update. OR Spectrum, 30(1), 1-52.

[86] SteadieSeifi, M., Dellaert, N. P., Nuijten, W., Van Woensel, T., and Raoufi, R. (2014). Multimodal freight transportation planning: A literature review. European Journal of Operational Research, 233(1), 1-15.

[87] Stowers, C. L., Palekar, U. S. (1993). Location models with routing considerations for a single obnoxious facility. Transportation Science, 27 (4): 350–362.

[88] Transport Canada (2011) Transportation in Canada—2011 Annual Report. Available at: http://www.tc.gc.ca. (Accessed April 18, 2013).

[89] TSB, 2004. Transportation Safety Board of Canada, statistical summary railway occurrences 2004, http://www.tsb.gc.ca/en/stats/rail/2004/statssummaryrail04.pdf (Accessed April 18, 2014).

[90] UNCTAD (2012) Available at: http://unctad.org/en/PublicationsLibrary/rmt2012_en.pdf (Accessed January 18, 2013).

[91] UNCTAD (2013) Available at: http://www.bandic.hr/download/unctad%20rmt2013_en.pdf (Accessed May 8, 2014).

[92] US Commodity Flow Survey (2007) Available at: http://www.census.gov/prod/2010pubs/ec07tcf-hm.pdf (Accessed April 18, 2013).

[93] US Department of Transportation, 2014. https://hip.phmsa.dot.gov/ (Accessed April 18, 2014).

[94] US Environmental Protection Agency. (2013) Electronic code of federal regulations (e-CFR), Title 49: Transportation, Subpart A— Applicability, General Requirements, and North American Shipments.

[95] Verma, M., and Verter, V. (2007). Railroad transportation of dangerous goods: Population exposure to airborne toxins. Computers & Operations Research, 34(5), 1287-1303.

[96] Verma, M. and Verter, V. (2010). A lead-time approach to planning rail-truck intermodal transportation of dangerous goods. European Journal of Operational Research, 202: 696–706.

[97] Verma, M., Verter, V. and Zufferey, N. (2012). A bi-objective model for planning and managing rail-truck intermodal transportation of hazardous materials. Transportation Research Part E, 48: 132–149.

[98] Verter, V. (2011). Hazardous Materials Transportation. Wiley Encyclopedia of Operations Research and Management Science.

[99] Wang, J., Kang, Y., Kwon, C., and Batta, R. (2012). Dual toll pricing for hazardous materials transport with linear delay. Networks and Spatial Economics, 12(1), 147-165.

[100] Wen, U. P., and Hsu, S. T. (1991). Linear bi-level programming problems--A review. Journal of the Operational Research Society, 125-133.

[101] Xie, Y., Lu, W., Wang, W. and Quadrifoglio, L. (2012). A multimodal location and routing model for hazardous materials transportation. Journal of Hazardous Materials, 135– 141.

[102] Yang, H, and Yagar, S. (1994). Traffic assignment and traffic control in general freeway-arterial corridor systems. Transportation Research Part B: Methodological, 28(6), 463-486.

[103] Yang, H., Yagar, S., Iida, Y. and Asakura, Y. (1994). An algorithm for the inflow control problem on urban freeway networks with user-optimal flows. Transportation Research Part B: Methodological, 28(2), 123-139.

[104] Yin, Y. (2000). Genetic Algorithm based approach for bilevel programming models. Journal of Transportation Engineering, 126(2), 115-120.

[105] Zhang, J. J., Hodgson, J., Erkut, E. (2000). Using GIS to assess the risks of hazardous materials transport in networks. European Journal of Operational Research, 121 (2): 316–329.