A Study on Routing and Scheduling of Hazardous Materials in Railway Transportation

Omar Abuobidalla

A Thesis

in

The Department

of

Mechanical, Industrial and Aerospace Engineering

Presented in Partial Fulfillment of the Requirements

for the Degree of

Doctor of Philosophy (Industrial Engineering) at

Concordia University

Montréal, Québec, Canada

October 2019

CONCORDIA UNIVERSITY
SCHOOL OF GRADUATE STUDIES

This is to certify that the thesis prepared

By: Omar Abuobidalla

Entitled: A Study on Routing and Scheduling of Hazardous Materials in Railway Transportation

and submitted in partial fulfillment of the requirements for the degree of

Doctor of Philosophy (Industrial Engineering)

complies with the regulations of the University and meets the accepted standards with respect to originality and quality.

Signed by the final examining committee:

Dr. Luis Amador	Chair
Dr. Ming J. Zuo	External Examiner
Dr. Zhi Chen	External to Program
Dr. Onur Kuzgunkaya	Examiner
Dr. Daria Terekhov	Examiner
Dr. Mingyuan Chen	Thesis Co-Supervisor
Dr. Satyaveer Chauhan	Thesis Co-Supervisor

Approved by ______________________
Dr. Ivan Contreras, Graduate Program Director

November 7, 2019

____
Dr. Amir Asif, Dean
Gina Cody School of Engineering & Computer Science

Abstract

A Study on Routing and Scheduling of Hazardous Materials in Railway Transportation

Omar Abuobidalla, Ph.D.

Concordia University, 2019

Railway transportation of hazardous materials including Toxic Inhalation Hazard, is crucial to North American economy. Although railway companies have favorable safety records in moving hazardous materials shipments, the possibility of spectacular events resulting from multicars incidents, however low, does exist, and the consequence can be potentially catastrophic in multiple fatalities. The rail disaster in Lac-Mégantic, Quebec, resulted in 47 fatalities and around $1.5 billion damages in 2013, is an example of low-probability high-consequence event. In this dissertation we aim at the development of analytical approaches considering the risk associated with hazardous materials in railway transportation. We study three versions of trip plan problems in the presence of hazardous materials, denoted as *hazardous materials trip plan problems*. In the first part of this dissertation we incorporate the blocking and train makeup decisions into the hazardous materials trip plan generation process, while limiting the total population exposures and environmental damages below the given thresholds. In evaluating the risk, we use aggregate measures, i.e., population exposures and environmental damages. We propose a non-linear mixed integer programming formulation for the considered problem. The solution of the model is NP-hard. In order to solve realistic size problem instances, a heuristic method is proposed by decomposing the problem into freight-to-block and block-to-train assignment problems. We then investigate more realistic hazardous materials trip plan problems by relaxing some of the assumptions. In the second part of this dissertation we incorporate risk-spreading functions into trip plan generation process and train scheduling decisions. For each risk-spreading function, we present a mathematical formulation and then we design a heuristic method to solve realistic size problem instances. We continue this study by introducing joint hazardous material trip plan and pricing problems. We also relax the assumption of the information of the customer requests are known in advance. Accordingly, we introduce different categories of customers with the definition of specific treatment for each of them including accept/reject basis and particular delivery and price regulations. In particular, we grouped customer requests into two classes as follows: (a) traditional customers, who sign long term contracts with the carrier, must be fulfilled by the carrier's own services, and their delivery and price quotations are set in advance and not subject to change; and (b) irregular customers, who make request for a carload moves less frequently and on an irregular basis, maybe outsourced/rejected because of (1) lack of train capacities, (2) additional risk exceeds the given risk thresholds, or (3) service level requirements. We propose two-phase heuristic to solve the considered problem. In the first phase, we solve a deterministic transportation planning and train timetabling problem for the known demands in advance. In the second phase, an optimization-based problem is built and solved at the arrival of the new request. Eventually, the dissertation ends with conclusion and further research recommendations.

Dedication

TO MY PARENTS, BROTHERS AND SISTERS FOR THEIR LOVE, CARE, SUPPORT AND PATIENCE

TO MY FRIENDS WHO ALWAYS ENCOURAGED ME

TO MY BELOVED FIANCÉE AND HER FAMILY FOR THEIR LOVE, SUPPORT, CARE AND PATIENCE

Acknowledgments

In the Name of God, Most Gracious, Most Merciful...

I would like to express my sincere and earnest gratitude to my supervisors, Prof. Mingyuan Chen and Prof. Satyaveer S. Chauhan, for their guidance and all the insight comments and full time supports. I would like to thank them for their constructive criticisms throughout my PhD journey at Concordia University. They were always willing to help me and I was not able to finish this journey without their support. They spent many hours of their time to teach me and guide me. The original idea of this dissertation is coming from Prof. Mingyuan Chen and Prof. Satyaveer S. Chauha and their deep insights helped me at different stages of my research.

I have been also very fortunate to have Professor Zhi Chen, Professor Daria Terekhov, Professor Onur Kuzgunkaya and Professor Ming J. Zuo for serving as my PhD committee members. They have provided me with inspiration, advice, and support to address the challenges through different stages in my PhD program. Many thanks to the administration staff at Mechanical, Industrial and Aerospace Engineering (MIAE).

My sincere thanks go to Dr. Mahmoud Awad, Dr. Noha M. Hassan from Department of Industrial Engineering in American University of Sharjah, Prof. Tarik Aouam from Department of Business Information and Operations Management in Ghent University, Dr. Murad Al-Rajab, Prof. Mama Chacha from Department of Mechanical and Industrial Engineering in ALHOSN University, Prof. Hamdi Sheibani from College of Engineering in Abu Dhabi University and Dr. Hussameldin Ibrahim from Department Industrial & Process Systems Engineering in University of Regina for their support and encouragement.

Their support and advice contributed to the entire outcomes of this work. To my wonderful colleagues and friends, Jair Ferrari, Marta Romeiro, César Rodríguez, Dr. Bai Qingguo, Dr. Zhifeng Zhao, Dr. Abdullahi Gujba, Dr. Chaoqun Dong, Dr. Qiong Wei, Dr. Armaghan Alibeig, Ladan Zamirian, Yasser Ghamary, Tiansheng Zhang, Ruo Liang, Hamid Reza, Amir Reza and Zenan Zhang, thank you very much. My family members and all my relatives supported and prayed for my success in this task. Their efforts are gratefully acknowledged. Thanks to my beloved fiancé (Walaa Awad) and her family members for their continuous support and encouragements. To my friends, I thank all of them. I gratefully acknowledge the financial support provided by Concordia University, Natural Sciences and Engineering Research Council of Canada (NSERC) Discovery grants, Canadian National (CN) Railway Scholarship and Concordia ENCS Funds for Research Students (FRS).

Contents

List of Figures

List of Tables

Chapter 1

Introduction

1.1 Overview

Railway transportation of hazardous materials (hazmat) including Toxic Inhalation Hazard, is crucial to North American economy supporting the national supply chain. Railway carriers transport a large quantity of hazardous materials in addition to transporting non-hazmat freights. According to recent statistics in 2012, railway companies transported around 111 million tons of hazmats in the United States (DOT, 2017b) and 26 million tons of hazmats in Canada (Searag et al., 2015). The impact potentially harmful to human health and environment, in the event of derailment or accident causing hazmat releases, is quite large. According to the U.S. department of transportation, the annual cost of hazamts release incidents in the Federal Railroad Administration (FRA) railway is about $19.6 million as shown in Figure 1.1. In North American, the two most frequently shipped hazardous materials that become airborne in the event of an accidental release are chlorine and ammonia. Chlorine is mainly used for purifying potable and wastewater and also used in as chemical intermediary in different industries for goods ranging from PV pipes to shampoo. Ammonia is a commercial fertilizer and mainly used in agricultural farms. Some of the hazmat trains are regularly routed near the urban areas. Train accidents or derailments pose a significant security threat (Branscomb et al., 2010). The rail disaster in Lac-Mégantic, Quebec, resulted in 47 fatalities in 2013, is an example of low-probability high-consequence

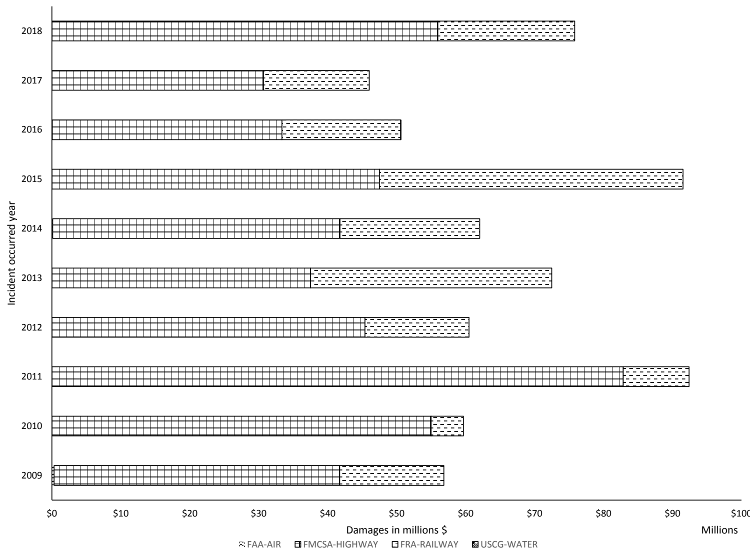
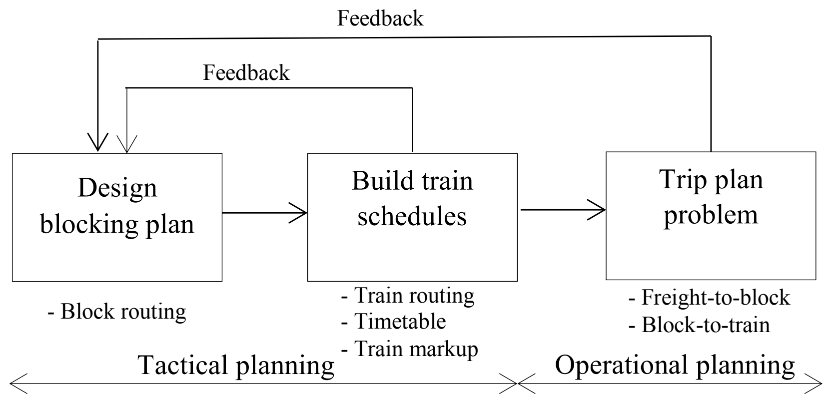


Figure 1.1: Accident/Derailment damages per mode.

event.

Railway operation processes in North America and European railway freight transportation differ from each other. In North America, carload service segment continues to be one of the rapidly growing railway business of the transportation industry (Van Dyke and Meketon, 2015). One of the prominent features of North America's railway industries is to use double consolidation, railcars are moved together to make the blocks and then blocks are grouped to make the trains. At the tactical level of planning, railway operators often develop blocking plans based on the expected demands. A large number of freight cars are grouped into blocks for economic and operational reasons (Barnhart et al., 2000). A block is a group of railcars that are assembled and move together from a common origin to destination. At the block destination yard, the block is separated and the freights are either delivered to their end customers or regrouped to build a new block. In many cases, blocks are pulled from its origin to destination yard by a single train service. However, some blocks may require to change train service through intermediate terminals. Solving train routing and scheduling problem must determine train routes, timetables, and train frequencies decisions (Khaled et al., 2015) as well as consolidate the blocks into services known as a train makeup plan (Jha et al., 2008). In classical trip plan problem, a set of commodities must be picked up at their origins, classified at their release times and delivered at their destinations with required time periods by a sequence of train services. Railcars in a block may pass some intermediate yards but will not be reclassified until the block has been delivered to its destination. The block destination might represent the end point of the journey of some railcars or an intermediate stop in the path of others that will be sorted again and regrouped to subsequent blocks. Customers usually require different service requirements in term of transit time and reliability (Kwon et al., 1998). In most cases, price and delivery quotations are set by contract between the customer and the carrier and are not announced. These quotations, specified based on the amount of supply and demand and relationship between negotiation parties, are not subject of change. However, if a customer requires an addition service, the carrier negotiates the price and delivery quotations and other terms of transportation including any special handling or operational requirements for hazmat. In some cases, a scheduled shipment may be also postponed to release train capacity for other shipments requiring higher service levels or to reduce the transport risk associated with hazmat transportations (if any). Trip plan can be classified into static and dynamic trip plans. In static trip planning problem, a blocking path and the sequence of blocks to which a commodity is assigned, are defined based on the class, the origin and destination of the commodity. A shipment is assigned to the earliest available train service at the terminal if the capacity of train is satisfied. If a train has reached its capacity limit, it may cause delays until the next train service is available. In dynamic planning, the railway operator may generate the trip plan of the commodities considering train capacities and may be frequently revised the schedule of the already existing scheduled demands when new information revealed, i.e., new customer request arrives. Optimized solutions of train planning problems based on integrated mathematical models are typically preferred to those based on a sequential solution approach (Zhu et al., 2014). A summary of the process of designing operation plan in North America railway industries is given in Figure 1.2.

Figure 1.2: Process of designing operation plan.



The risk associated with an accidental or incident releases of hazmats is the main difference in transportation of hazmats from the regular shipment. The prevailing studies are assessment of the transport risk associated with a shipment and then obtaining the set of routes that minimizes the risk. The resulting minimum risk route is typically compared with the minimum cost route, assuming that carrier taking into account the risk. Various risk assessment functions have been proposed in Erkut and Verter (1998). The most popular risk assessment function used is the *traditional risk model*, which is defined as the product of two quantities: (a) the probability of an incident that cause hazmat releases; and (b) the consequences of the incident. Saccomanno and Chan (1985) and Abkowitz et al. (1992) consider the probability of having a hazmat incident along its itinerary. This risk assessment is more suitable for hazmats with relatively small consequences. Batta and Chiu (1988) define the transport risk as the number of people living within a threshold distance from the route. This model does not include the probability of an incident and it is more suitable for hazmats with relatively low probability of high consequences such as TIH materials. In this dissertation, we focus on hazardous materials that become airborne in the event of an accidental release. We use the consequence to measure the transport risk associated with hazardous material transportations. In particular, we use the air dispersion models, Gaussian Plume Model and Box Model, for population and environmental risk calculation. The former quantity is the number of inhabitants involved in the consequential effect of a release from a hazmat transport derailment, whereas the latter measure is the total environmental damages due to hazmat leak. The consequences depend on a number of factors including number of hazardous materials cars (Verma and Verter, 2007), train speed (Fang et al., 2017), train length (Bagheri et al., 2012), and placement of hazardous materials cars (Cheng et al., 2017). The dispersion of pollutants with the incident area is a function of weather parameters such as the wind direction, wind speed, and atmospheric stability. The immediate dangerous life and health level (IDLH), defined as the exposure to airborne contaminants that is likely cause death or immediate or long term health effect, depends on the chemical characteristics of hazmat and the volume of the hazmat in train (Verma and Verter, 2007). According to the National Institute for Occupational Safety and Health (NIOSH), the IDLH for propane exposure are 4,200,000 ppm for fatality and 600,000 ppm for injuries. At certain IDLH, the operator needs to identify a safety distance threshold.

Optimizing mathematically the train operational planning process will be more beneficial when the trip plan problem considers the risk associated with hazmat freights transportation. In such cases, the operator also needs to decide (a) frequency of train services and trip plan of freights, (b) positions of hazmat freights in the blocks, (c) sequence of blocks on the train services, and (d) speed of each train service and schedule of each freight in order to reduce the transport risks associated with hazmat transportation while satisfying operational constraints. Hazmat shipment schedule may also need to be frequently revised due to changes of population sizes and/or atmospheric conditions along the routes. Following a well defined freight operation plan may not only helpful in reducing the operation costs but also may diminish the transport risk associated with hazmat transportation (Bersani et al., 2016).

In many countries, hazmat transportation is typically regulated by the governments due to the associated population and environmental risks with their transportations. It is common to assume that there is a regulator that manages the hazmat transportation on the network under its jurisdiction. The regulator, in contrast with the single carrier, usually considers a hazmat transportation problem that involves multi-commodities, multiple origin-destination demands, and multiple carriers route selection decisions. The main

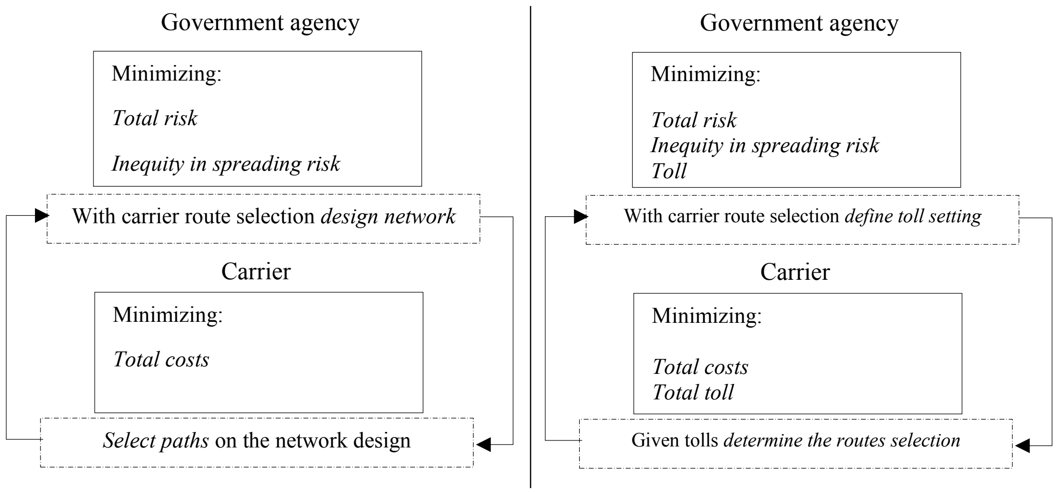


Figure 1.3: Hazmat network design vs Toll setting.

concern for a regulator is to limit the risk induced by the hazmat transportation over the population and the environment. In addition to the minimization of the total population exposure, the regulator may also promote risk spreading over the population and environment. As the regulator often does not have the right to impose specific itinerary to carriers, it can only mitigate transportation risk by means of strategies regulate the use of train segments for hazmat shipments. Two possible strategies are used. In the first strategy (illustrated in the left side of Figure 1.3), the regulator has the right to close certain train segments to hazmat trains or to limit the amount of hazmat freights to a given risk thresholds (road transportation (Esfandeh et al., 2017; Kara and Verter, 2004); rail industry (Chin et al., 2009)). In the second strategy (illustrated in the right side of Figure 1.3), the regulator uses itineraries or links tolls to deter the carriers from using certain train segments and consequently motivates them to route their shipments on less risky links (road transportation (Marcotte et al., 2009); rail industry (Assadipour et al., 2016)). In this approach, the regulator motivates the carrier from using less risky train services and the carrier avoid any increase in the transportation costs. In this dissertation we study three versions of the hazardous materials trip plan problems from a single railway operator perspective. A railway operator, a central decision maker, is in charge to manage various customer requests for a carload moves within a railway network. The operator receives a sequence of future requests for carload moves both hazmat commodities as well as regular commodities. In compliance with the railway policy and government regulation, the operator assesses the risk associated with hazmat transportation when generating trip plans in addition to the costs for serving customer requests. Details of the three hazardous material trip plan problems will be discussed in subsections 1.2.1-1.2.2.

1.2 A study of hazardous materials trip plan problems

The purpose of this thesis is to provide analytical approaches for planning railway freights including regular and hazmat commodities. In this dissertation, we study three versions of *Hazardous Materials Trip plan Problems* (HTPs). Each version of HTPs involves different features, risk functions, assumptions and decision variables. In the classical HTPs, a set of commodities must be picked up at their origins, sorted at their release times and delivered at their destinations with required time periods while the transporting risks associated with hazardous materials below the given risk thresholds. The three versions of HTPs are sufficiently distinct in required inputs, outputs, solution time, and planning level. It is important to understand both, the similarities and differences between the three rail freight transportation planning problems.

1.2.1 A study of HTPs with blocking decisions

Rerouting of hazmat commodities is one of the main issues in hazmat transportation literature (Glickman et al., 2007). Traditional problem solving approaches without considering the blocking and train makeup decisions may have limited capabilities to adapt operation plans. Existing literature revealed that blocking, train makeup, and rail freight transportation decisions in freight railway operations are interrelated. However, research on hazardous materials trip plan models incorporating explicit blocking and train makeup plans is limited (Erkut et al., 2007; List et al., 1991). Chapter 2 aims to answer the research questions: (a) how to determine simultaneously the blocking, train makeup and freight transportation plans such that the total costs from serving the demands is minimized while the population and environmental risks below the given thresholds and (b) what is the effect of incorporating the hazardous materials demands into trip plan generation process. To find answer to these questions, in the first part of this dissertation we propose a compact mathematical model to integrate the blocking and train makeup decisions into trip plan generation process denoted as *HTPs with blocking decisions*. Solving the HTP with blocking decisions is to make simultaneously the blocking, train makeup, and freight transportation decisions to provide the required services to customers and to minimize total cost including the costs of earliness, tardiness, classification, and holding cost associated with fulfilling all the demands. The risks associated with transporting hazmats are considered by imposing risk threshold constraints. We make of use of aggregate measures of risk, i.e., population exposure and environmental impacts. The Gaussian Plume Model (GPM) and Box Model (BM) for air dispersion are used for population exposure and environmental risk calculation. For efficient computation, we use piecewise linear functions to substitute the nonlinear hazmat risk functions in GPM and BM. The solution of the problem is to determine for each customer request (a) the itinerary that must follow from its origin to destination (if served), (b) the sequence of trains that it will be assigned to along the route, and (c) the blocks used to transport it for each train leg along its route (known as the blocking path). This makes the HTPs with blocking decisions more challenging than classical HTPs as the routing and scheduling decisions of the demands must be simultaneously determined with blocking and train makeup plans. Hence, HTPs with blocking decisions generalize the HTPs as they incorporate the blocking decisions to the trip plan generation process. In presenting the model, a multi-layer approach is followed similar to that in Zhu et al. (2014). The model presented is formulated considering three layers corresponding to services, blocks and railcars, respectively. An itinerary of a demand is a path in the three-layer network. We design two matheuristic methods to solve the considered problem by decomposing the problem into freight-to-block and block-to-train assignment problems, which can be solved efficiently. While Chapter 2 aims to find a comprehensive operational plan for serving regular and hazmat commodities such as the total risks below the given thresholds, the distributing of the transport risk over population is the subject of Chapter 3. We also aim to answer the following research questions: (a) what is the effect of incorporating risk distribution function into trip planning process, (b) what is the best risk distribution function to equitable spread the risk over the population, and (c) how the railway carriers can reach high level of risk spreading while the total population exposure within a given threshold.

1.2.2 A study of HTPs with train scheduling decisions

The classical HTPs suffers from some limitations. The trip plans generated by the operator are typically made without taking into account risk spreading function. It may happen that certain population of the transportation network tend to be overloaded with hazmat transportations, even if the total transport risk is below the given thresholds. This may result in a significant increase of the incident probability. Risk spreading might be interpreted as a further objective to be attained, without overloading any train service or part of the network. Another limitation is that the classical HTPs assume the train scheduling decisions are given. As mention earlier, the population density and atmospheric stability parameters typically vary over time. When the freight car routing and scheduling problems are solved separately, it may be challenging to find a timetable that satisfies a set of operation constraints and risk thresholds constraints. A chance to overcome those limitations is to consider risk spreading function and train scheduling decisions into trip plan generation process. Taking proper train scheduling plan is not only important to reduce the operation costs for serving demands (Ireland et al., 2004) but also may decrease the transport risk associated with hazmat transportation (Fang et al., 2017).

In the second part of this dissertation we investigate the integration of train scheduling decisions into trip plan generation process considering risk spreading function, refereed to as *HTPs with train scheduling decisions*. In this version of HTPs, we relax the assumption of the schedule of the train services is given. We also introduce the risk-spreading functions to distribute the risk over the population. The main concern for the operator is controlling the risk exposed to the populations. We consider the problem of minimizing the weighted sum of the cost of serving the commodities plus risk distribution function using well-defined measures, either the maximum population exposure, the difference between the maximum and minimum risk, or the mean absolute deviation of the risk while limiting the population exposure below the given risk thresholds. The solution of the problem is to determine for each demand (a) the itinerary that must follow from its origin to destination yard (if not outsource) including the blocking path, (b) the sequence of trains that it must assign along the route so that the trains capacities constraints, and risk thresholds are satisfied, and also determines the timetable of planned train services. We propose non-linear mixed integer programming models and a heuristic method for preparing the shipment plans and determining the schedule of train services. The heuristic generates itineraries associated with much higher levels of risk-spreading quantity than those dispatching strategies without considering risk-spreading function. Numerical examples are provided to study and analyze different risk distribution functions.

1.2.3 A study of HTPs with pricing decisions

The above versions of HTPs made some important assumptions. The list of demands information is assumed given in advance and deterministic. In fact, transportation requests fluctuate during the actual planning. For example, some demand requests revealed at midst of the operation. The operator may revise the itineraries for the already existing scheduled demands to reduce the train capacities for certain train services or the risks associated with hazmat transportation (if any). Another limitation is that the classical HTPs ignore the revenues generated from serving the requests and focus on costs resulting from routing and scheduling the demands. In general, this assumption expresses the implicit hypothesis that the total costs from rerouting of hazmat demands will be compensated by the total revenue generated. Such an assumption does not necessarily hold, and incorporating pricing decisions have important implications in the total net profit obtained (Crevier et al., 2012) and population exposure as well (Bianco et al., 2012; Marcotte et al., 2009).

In the last part of this dissertation, we study a freight car scheduling and train dispatching problem involving hazmat transportation. In many railway companies, rail shipment prices are set by contract between the customer and the carrier and are not announced. The price quotations are not subject to change. However, if the customer requires to ship extra commodities, the carrier may increase the shipping rates to compensate the additional loads and risk associated with hazmat transportation (if any). Chapter 4 aims to answer the following research questions: (a) what are the impact of accepting additional hazardous materials commodities after preliminarily schedules have been developed for the already existing scheduled demands, (b) what is the best strategy to deal with dynamic planning of operations in response to changing demands after preliminary schedules have been developed for hazardous materials demands and (c) what are the economic benefits from adopting dynamic planning of operations in response to changing demands. To answer these questions, we consider different categories of customers with the definition of specific treatment for each of them, including accept/reject basis and particular delivery and price regulations. In the considered problem, customer requests known in advance will be scheduled first. Additional requests, after the preliminary schedule is generated, may be accepted from new customers. Depending on available capacities, the generated schedule, and the additional transport risk, new customers may be quoted with different prices and time to deliver. We propose two-phase heuristic solution method to solve a real-size problem instances. In the first phase, we solve the integrated train timetabling and deterministic freight transportation problem for the known requests in advance. The solution determines the timetables of the train services and best demand-itinerary assignment decisions. In the second phase, a real-time optimization problem is built and solved at the arrivals of new freight requests, denoted as *HTPs with pricing decisions.* Numerical examples are provided and managerial insights are drawn to compare four pricing strategies. A summary of the freight car scheduling and train dispatching problems and their main features is given in Table 1.1.

Table 1.1: A summary of the considered HTPs.

Main features	*HTPs with blocking decisions*[2]	*HTPs with train scheduling decisions*[3]	*HTPs with pricing decisions*[4]
Tactical decisions			
train scheduling plan		X	X
blocking plan	X		
train makeup plan	X		
Operational decisions			
freight-to-block decisions	X		
freight-to-train decisions	X	X	X
Pricing decisions			
part of the decision process			X
Objective			
pure cost-oriented	X	X	X
pure profit-oriented			X
risk spreading function		X	
Constraints			
train capacity	X	X	X
block capacity	X		
track capacity		X	X
population exposure threshold	X	X	X
environment damage threshold	X		
service commitment	X		X
Risk reduction strategy			
rerouting of hazmat risk	X	X	X
partner service	X	X	X
hazmat network design(blocking)	X		
scheduling decisions	X	X	X
pricing decisions			X
Solution method	X[a]	X[b]	X[c]

[a]*Matheuristic method*; [b]*heuristic method*, [c]*Phase* 1: *a matheuristic method and Phase* 2: *heuristic method.*

1.3 Scope and objectives

In this dissertation we aim at the development of analytical approaches considering the risk associated with hazardous materials transportation from a single carrier perspective. In particular, we aim to introduce and study: (a) HTPs with blocking decisions, (b) HTPs with train scheduling decisions, and (c) HTPs with pricing decisions. The specific objectives of this research are summarized as follows:

- To study the HTPs with blocking decisions. The problem integrates the blocking, train makeup, and freight routing and scheduling decisions. We present a nonlinear mixed-integer programming (NMIP) and propose two matheuristic methods to solve the HTPs with blocking decisions.

- To study the HTPs with train scheduling decisions. We present a nonlinear mixed-integer programming model and propose heuristic method to solve HTPs with train scheduling decisions.

- To study the HTPs with pricing decisions. We present a nonlinear mixed-integer programming and propose two-phase heuristic to solve the consider problem.

1.4 Co-authorship statement

I, Omar Awni Abuobidalla, hold a principal author for all the manuscripts chapters in this dissertation. However, each of the manuscripts is co-authored by my supervisors, Prof. Mingyuan Chen and Prof. Satyaveer S. Chauhan, whose contributions have greatly facilitated the development of the ideas in the manuscripts, the development of solution methods, the managerial insights of the computational experiments and the manuscripts writing.

Bibliographical note. Chapter 2 contains results from Abuobidalla et al. (2019c). Also, the results was presented at (a) 2017 OPTIMIZATION DAYS Conference, (b) 2018 OPTIMIZATION DAYS Conference and accepted at 2017 International Conference on Operations Research (ICOR). Chapter 3 contains results from Abuobidalla et al. (2019b) and to be presented at 2020 OPTIMIZATION DAYS Conference and the 22nd Conference of the International Federation of Operational Research Societies (IFORS 2020). Chapter 4 contains results from Abuobidalla et al. (2019a) and to be presented at 2020 Canadian Operational Research Society (CORS) Conference.

Newspaper interviews myself with Dr. Mingyuan Chen and Dr. Satyaveer S. Chauhan. (a) Danger rerouted: A Concordia engineering project could limit the impact of rail accidents available at (Concordia website) *http://www.concordia.ca/cunews/main/stories /2016/04/18/new-jmsb-research-could-limit-impact-of-rail-disasters.html*

(b) Concordia University engineers are hoping mathematical model will help rail operators avoid potential problems available at (CBC website) *https://www.cbc.ca/news/canada/montreal/lac-megantic-four-years-researchers-prevention-1.4191819*

(c) Predicting rail disasters with math which has been picked up by several news media *http://www.concordia.ca/cunews/main/items/2017/7/10/newsmaker.html*

(d) Record amount of Canadian oil exported by rail raises safety concerns (Global News) *https://globalnews.ca/news/4824795/canadian-oil-exports-rail-safety/*

Appreciation letter (August 2017) from president and vice-chancellor of Concordia university (Prof. Alan Shepard).

1.5 Contributions of this thesis

This thesis presents a number of main contributions in modeling and methodology that differentiate our work from the existing literature. First, we consider simultaneous decisions regarding blocking, train makeup, and freight transportation plans in the presence of hazmats commodities to reduce hazmat transport risk. We proposed a compact mathematical formulation to integrate the blocking and train makeup plans into trip plan generation process. The problem captures most features of the operational planning problem in real-world railway industries operating on double consolidations. On the other hand, the problem is still a simple version of real-world railway planning problem in that it also need to integrate issues such as empty rail car distribution plan, the sequence of hazmat in a block and the sequence of blocks in train, and locomotive assignment problem. A heuristic method is developed to solve a real-size problem instances by decomposing the original problem into freight-to-block and block-to-train assignment problem in reasonable computation times. Secondly, we introduce a risk spreading function based on variability to avoid overloading of the transport risk on a certain population zone. The carrier's objective function incorporates both the cost of serving the commodities and risk spreading function. For each risk spreading function, we propose a nonlinear mathematical model and then design a heuristic method to solve a real-size problem instances. We also assess the tradeoffs between the total cost of serving the demands and the risk spreading. Thirdly, we introduce hazardous material trip plan problem and pricing decisions for new incoming requests. We develop a methodology for joint capacity allocation and dynamic pricing problems considering the transport risk associated with hamzat transportation and design a heuristic to solve real-size problem instances. Different pricing strategies are compared considering the transport risk associated with hazardous material transportation.

The title of the manuscripts resulted from this dissertation and potential contributions are given below:

A Matheuristic Method for Planning Railway Freight Transportation with Hazardous Materials

(*This manuscript has been published in Journal of Rail Transport Planning & Management, Vol.10, 2019, pp. 46-61. https://doi.org/10.1016/j.jrtpm.2019.06.001.*)

- Introduce hazardous materials trip plan models incorporating explicit blocking decisions which captures most features of the operational planning problem in real-world rail companies operating on double consolidations and design a heuristic to solve HTPs with blocking decisions.
- Develop a methodology to determine a comprehensive operational plan including the (a) blocking, (b) train makeup and (c) rail freight transportation planning problems in the presence of hazmat commodities.
- Provide railway operators with analytical approach to plan regular and hazmat freights while considering the risk associated with hazmat transportation.
- Integrate environmental damage and population exposure into trip plan generation process as research on this area is limited.
- Use piecewise linear functions to substitute the nonlinear hazmat risk functions in Gaussian Plume Model and Box Model for efficient computations.

An Integrated Train Scheduling and Hazardous Materials Trip Planning Problem

(*This manuscript is under review in International Journal of Rail Transportation (September 2019)*)

- Develop a methodology to determine an operational/tactical plan including the (a) schedule of train services and (b) trip plan of the commodities while spreading the transport risk over population, which in turn could be a very valuable tool for railway operators.

- Develop a risk spreading function based on variability of population exposure to distribute the risk more equitably in railway network and design a heuristic to solve HTPs with train scheduling decisions. We compared the results from different risk spreading functions.
- Integrate different risk reduction strategies into trip plan generation process such as rerouting of hazmat and using the partner services which in turn could be a very useful tool for practitioners for cases where they face scarce resources and/or limited risk thresholds. Each strategies has its beneficial in reducing transport risk and corresponding cost of implementation.

An Integrated Hazardous Materials Trip Plan Problem and Pricing Decisions for Railway Supply Chain System

(*This manuscript is under review in Research in Transportation Business & Management (August 2019)*)

- Support the development of a risk-based approach for the rail operators to decide the price and delivery quotations for new customer requests which facilitates the negotiation process between the operator and customers.
- Develop a methodology for joint capacity allocation and dynamic pricing problems considering the transport risk associated with hamzat transportation and compare different pricing strategies.
- Develop a scheduling tool to help railway operators optimize the routing and scheduling of regular and hazmat commodities and dynamically allocate the shipment to train sequences as information of demands are revealed.
- Assess the savings by comparing the schedules developed using FIFO with the schedule produced by the proposed procedure.

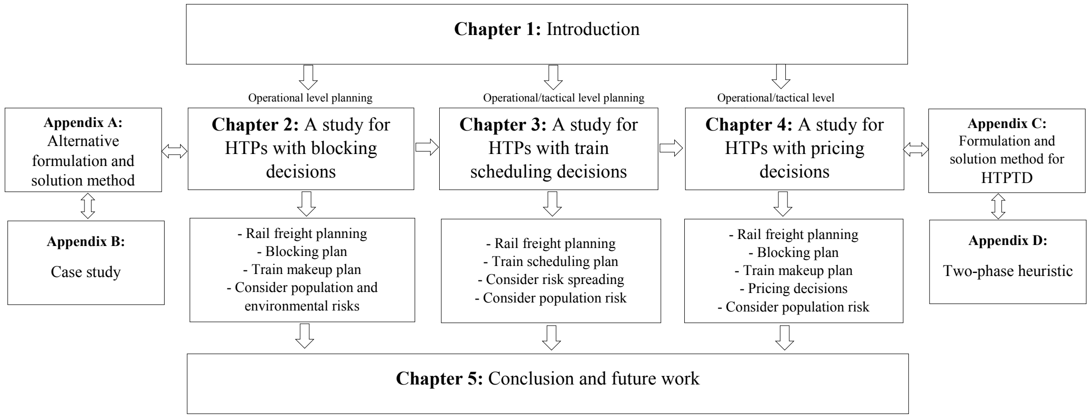


Figure 1.4: Organization of the thesis.

1.6 Organization of the thesis

This thesis is organized as follows (illustrated in Figure 1.4). Chapter 2 presents hazardous materials trip plan problem with blocking decisions and introduce two matheuristic methods and present several numerical examples. Section 2.3.1 gives the formal definition of the problem. Section 2.3.2 presents the modeling assumptions and developed a mathematical model with detailed explanations. The developed solution procedure, including a preprocessing phase and a heuristic method, is presented in Section 2.4. Numerical example problems are presented with results analyzed in Section 2.5 to illustrate the proposed model and the solution procedure. Conclusions of this work are drawn in Section 2.6. Chapter 3 gives the definition of the hazardous materials trip plan problem with train scheduling decisions and proposes a heuristic method to solve the considered problem and presents some numerical examples. The considered problem is defined and the different versions of risk spreading considerations are presented in section 3.3. The proposed solution is described in section 3.4. We present our experimentation results in section 3.5. Conclusions of this work are given in section 3.6. Chapter 4 introduces hazardous materials trip plan problem with pricing decisions and describes a two-phase heuristic method and presents numerical examples. The considered problem is defined in section 4.3. The real-time methodology is described in section 4.4. Numerical examples are provided in section 4.5 to illustrate the considered problem. We conclude our research in section 4.6. The manuscript ends with summarizes the contents, reemphasizes the findings and also recommendations for future research direction are highlighted in Chapter 5.

Chapter 2

Modeling and solution method for HTPs with blocking decisions

A Matheuristic Method for Planning Railway Freight Transportation with Hazardous Materials

Omar A. Abuobidalla, Mingyuan Chen, Satyaveer S. Chauhan

This paper has been published in Journal of Rail Transport Planning & Management, Vol.10, 2019, pp. 46-61. https://doi.org/10.1016/j.jrtpm.2019.06.001.

Railway freight transportation planning problem aims at determining trip plans of transporting various commodity demands within given time periods. Since freight transportation is typically performed for a group of train cars or blocks, decisions must be made on proper or optimized blocking. Integrating blocking decisions into trip planning generation process is an interesting challenge problem that we address in this chapter. An optimization model is proposed to determine the route for a demand car to travel from its origin to destination, the blocks to be transported with and the sequence of trains to be assigned to, given the schedule of train services as well as train and yard capacities. The proposed model, similar to multicommodity network design model, has non-linear functions to represent hazardous material risks to be minimized. A preprocessing procedure is developed to reformulate the proposed model for more efficient computing and a heuristic solution method is designed for solving realistic freight transportation problem in practice. Numerical examples are presented to illustrate the developed mathematical model and the solution procedure.

2.1 Introduction

Railway transportation of hazardous materials (hazmat) including Toxic/Poison Inhalation Hazard (TIH/PIH), is crucial to North American economy supporting the national supply chain. According to recent statistics in 2012, rail carriers shipped almost 111 million tons of hazmat in the United States (DOT, 2017b) and 26 million tons of hazmat in Canada (Searag et al., 2015). The real danger and potential catastrophic consequences associated with railway hazmat transportation cannot be overlooked (Chin et al., 2009). The disaster caused by derailment of freight train carrying crude oil at Lac-Mégantic, Quebec in 2013, is an example of such low-probability high-consequence (LPHC) event. In addition, the growing volume of hazmat carried by trains and several train accidents causing crude oil spills have raised grave public and government concerns (Margolis, 2015). In Canada, carload service segment continues to be one of the rapidly growing railway business of transportation industry that shares from 20% to 50% of the overall traffic (Van Dyke and Meketon, 2015), in separated intermodal and dedicated unit train services. One of the key features of North America's railway supply chain systems is to use double consolidation. At the tactical level of planning, railway operators often develop blocking plans based on demand forecasts. A large number of freight cars are aggregated into blocks for economic and operational reasons (Ahuja et al., 2007b; Barnhart et al., 2000), to reduce handling costs and waiting times at terminals. At the block destination yard, the block is dismantled and the freights are either delivered to their end customers or regrouped to build a new block. Usually, blocks are pulled from its origin yard to destination by single train service. However, some blocks may require to change train service through intermediate terminals along their journeys (Xiao et al., 2018), known as block-swapping. Since block-swapping incurs block handling cost and delays, railway operators attempt to avoid them if possible. Solving a train journey design problem must consider train routes, timetables, and train frequencies (Khaled et al.,

2015) as well as consolidate the blocks into services known as a train makeup (Jha et al., 2008; Nozick et al., 1997b). In shipment scheduling, a set of commodities must be picked up at their origins, categorized at their release times and delivered at their destinations with required time periods. Customers may require different service levels with respect to transit time and reliability (Kwon et al., 1998). In certain cases, a scheduled shipment may be delayed in order to release train capacity for other shipments requiring higher service levels. A trip plan typically defines the itinerary of shipments from their origins to destinations, including freight-to-block and block-to-train assignment decisions. According to Van Dyke and Meketon (2015), there are two types of trip planning approach used by most North America railway companies: static trip plan and dynamic trip plan. In static planning, a blocking path and the sequence of blocks to which a commodity is assigned, are defined based on the class, the origin and destination of the commodity. A shipment is assigned to the earliest available train service at the terminal if the capacity of the train is satisfied. If a train has reached its capacity limit, it may cause delays until the next train service is available. The trip planning can be decomposed into routing and scheduling problems. When those problems are solved separately, it may be challenging to find a timetable that satisfies a set of operation constraints (Cordeau et al., 1998). Major railway operators in North America use MultiModal systems to generate the blocking path for each commodity. In dynamic planning, the railway operator may determine the route and schedule of the commodities using Automatic Blocking and Classification (ABC) algorithm considering train capacities. This is similar to the one used in CP Canada. If the initial schedule is disrupted due to, for example, a new shipment arrives, a new trip plan is generated. In practice, a hierarchical approach is often followed to solve the train scheduling and planning problem due to its complexity and large size of real-world problems. The original problem is decomposed into a series of subproblems to be iteratively solved in five steps (Ireland et al., 2004): (a) generate a traffic forecast, (b) solve the blocking problem, (c) design train plan on the blocking policy, (d) analyze yard and train workloads using a simulation model, and (e) develop the crew and locomotive plans. Since freight transportation business faces significant uncertainties and demand fluctuations (Crainic, 2000), traditional problem solving approaches may have limited capabilities to adapt operation plans (Kwon et al., 1998). Optimized solutions of train planning problems based on integrated mathematical models are preferred to those based on a sequential solution approach (Crainic et al., 1984; Haghani, 1989; Keaton, 1989; Zhu et al., 2014). Mathematically optimized solutions will be more useful when the considered problem involves hazmat freights transportation. In such cases, management also needs to decide (a) positions of hazmat freights in the blocks (Bagheri et al., 2011; Verma, 2011), (b) sequence of blocks on the train services (Cheng et al., 2017; Verma and Verter, 2010), and (c) speed of each train service and schedule of each freight (Fang et al., 2017) in order to reduce hazmat transportation risks while satisfying operational constraints. Hazmat shipment schedule may also need to be frequently revised due to changes of population sizes or atmospheric conditions along the routes in different time periods. Following a well defined freight operation plan may reduce not only operation costs (Ireland et al., 2004) but also risks associated with hazmat transportation. In this chapter, a non-linear integer programming model is proposed for planning hazmat transportation in a railway-based supply chain system. The solution of the model is to determine the blocking, train makeup, and freight-to-block assignment decisions. The results of several numerical example problems indicate that solutions obtained from the integrated model are closer to optimality than those based on sequential approaches.

2.2 Related literature

A considerable amount of research focusing on road transportation of hazmat is available as can be found, for example, in Erkut and Alp (2007a); Erkut and Ingolfsson (2000); Verter and Kara (2008); Zografos and Androutsopoulos (2004), among others, while research in railway transportation of hazmat is comparably less (Erkut, 1995; Erkut et al., 2007; List et al., 1991). Several researchers have investigated hazmat rerouting problems in railway supply chain systems (Bersani et al., 2016; Glickman et al., 2007; Verma and Verter, 2010; Verma et al., 2011). Two versions of the problem have been studied: the local routing and global routing. In local routing, risk management is restricted to a single OD shipment rather than the whole OD map. Glickman (1983) and Glickman et al. (2007) stated that population risk can be reduced by 25-50% when rerouting approaches are implemented at the cost of 15-30% increase in traffic intercity. The cost-risk-time trade-offs in rail-truck intermodal transportation systems were discussed in Verma and Verter (2008). Erkut et al. (2007) noticed that the local routing models fail to consider the nature of transport risk, i.e., population density and weather conditions. In global routing, the decision maker, a central authority that manages all customer requests for transportation within a railway network, evaluates the network risks by considering all OD shipments together using a mathematical model. The problem is usually formulated as a version of multi-commodity network design model aiming at minimizing total cost and risk. In solving most of the routing models as in Assadipour et al. (2015); Verma et al. (2011), the blocking plan and train makeup decisions are assumed known in advance. It has been shown that global routing problems are NP-hard and it is difficult to solve real-size problem instances using exact optimization (Marin and Salmeron, 1996). Also, there are additional complexities due to non-linearity functions to account for risk particularities in railway system. An approximation function was developed in Verma and Verter (2007) by extending the standard Gaussian Plume Model (GPM) to model risks caused by airborne hazmat freights such as chlorine, propane, and ammonia. Various heuristic and meta-heuristic methods were developed as presented in Verma and Verter (2010), Verma et al. (2012), Sarhadi et al. (2017), Assadipour et al. (2015), among others. Verma et al. (2011) pointed out that population exposure to hazmat can be reduced without scarifying cost advantage by initiating hazmat unit-train or running a mix of regular and priority trains. An extension of standard shortest path algorithm to incorporate population risk, transfer delays and time-dependence was presented in Chang et al. (2007). Chin et al. (2009) discussed rerouting of hazmats around the Washington DC in the US with shipment ban in that area. It can be noted that the above routing models are not intended to determine train departure times. Since these planning models do not take scheduling decisions into account, it may be challenging to determine a timetable for all planned trains satisfying terminal capacity and/or risk threshold conditions. Fang et al. (2017) studied hazmat routing and scheduling problems with shipment due dates and risk equity consideration. A lower bound scheme and heuristic method were developed to solve a large size problem. Sun et al. (2016) studied the problem of hazmat freight scheduling for truck-rail intermodal transportation with fixed scheduled services. The proposed model has a set of capacity constraints for each train service to minimize population exposure to hazmats and environment risk. A case study was conducted based on freight railway network in Bejing-Tianjin-Habei area in China. Saccomanno and El-Hage (1989) stated that the positions of hazmat freight cars in a train may affect the chances of hazmat releases in train derailment. Bagheri et al. (2012) argued that the current marshaling policy, known as location-based approach, to position hazmat freights to the blocks in most Class I rail transportation should be improved to reduce risk. Verma (2011) claimed that the front of a train service is unsafe and the 7th to 9th train deciles are the best positions for hazmat cars. Cheng et al. (2017) studied an integrated train makeup and hazmat rail car placement problem. The problem was modeled as an assignment problem with two main nested assignment decisions, the assignment of blocks to train slots and the assignment of commodities to positions in the blocks. The authors emphasized that there is a need for more studies on commodity-based blocking in comparison with those on location-based blocking. In some cases, selecting the best position of hazmat on trains may be part of a train makeup strategy (Verma and Verter, 2010). Rail transportation trip planning and scheduling problems have also been studied extensively by researchers. As discussed in Van Dyke and Meketon (2015), many North American railway operators use well developed algorithms to solve car scheduling problems in capacitated trip planning. For example, Fukasawa et al. (2002) studied railway planning problems for scheduling loaded and empty rail cars within given train schedules. Chang (2008) formulated an international intermodal routing problem as a multi-objective multi-modal commodity flow problem with time windows. The problem was solved using decomposition method. Moccia et al. (2008) studied multi-modal routing problems with timetables and time windows. As can be seen from those rail freight routing and scheduling problems in the literature, blocking, train makeup, and freight transportation decisions in freight railway operations are interrelated. In this chapter, a mathematical model is developed to decide simultaneously blocking, train makeup, and freight transportation decisions in the presence of hazmat freights. The considered problem captures most of features of the operational planning level of real-world railway companies operating on double consolidation. The proposed work has the following contributions. First, a non-linear mixed integer programming model is proposed for determining simultaneously the blocking, train makeup and freight transportation plans such as customer requests are fulfilled while the risks associated with hazmat shipments below the given thresholds. Second, different risk reduction strategies are incorporated for routing and scheduling hazmat freights, i.e., rerouting of the hazmat materials and using partner services. Finally, we develop heuristic-based method to solve several realistic-size problem instances.

The remainder of the chapter is organized as follows. Section 2.3.1 gives the formal definition of the problem. Section 2.3.2 presents the modeling assumptions and developed a mathematical model with detailed explanations. The developed solution procedure, including a preprocessing phase and a heuristic method, is presented in Section 2.4. Numerical example problems are presented with results analyzed in Section 2.5 to illustrate the proposed model and the solution procedure. Conclusions of this work are drawn in Section 2.6.

2.3 Problem assumptions and modeling

In this section, a hazmat trip planning problem (HTP) with blocking decisions is presented and a nonlinear mathematical programming model is introduced for solving the considered problem.

2.3.1 Problem statement

We consider a railway carrier that operates a set of scheduled services S. The origin, destination, capacity, service route, intermediate-stop, and the schedule of each service $s \in S$ have been predetermined by the service provider. The capacity of the service s, denoted by U_s, determines the maximum number of railcars can be hauled by a train. A fixed cost, the cost of locomotives and crews, is incurred to run the planned services. The operator faces a sequence of requests for carload moves, hereafter called demands, within a railway network. The demand is defined with a class of traffic $k = \{1, \ldots, K\}$. Each demand is composed of the origin yard o_k, destination yard d_k, type of commodity (i.e., hazmat or non-hazmat), quantity D_k including hazmat commodities H_k, expected time when the shipment is available at the origin τ_k^A, and a time window to arrive at the destination $\tau_k^W \in [\tau_k^E, \tau_k^L]$. At time τ_k^A, a demand will first be sorted and tentatively placed on a classification track. In order to fulfill a demand and avoid to re-classified the shipments, the carrier constructs a set of blocks $b \in B$, select one available path and decide the sequence of trains to use along the route. θ_b is the cost associated with constructing (or block-swapping) block b at its origin yard to occupy a track for τ_b^H time periods. The block-swapping cost incurred when a block is detached from a service and attached to another one. If the arrival time window of a demand is not satisfied, a penalty cost may occur. The penalty cost is proportional to both the demand's quantity and the delayed time. Out of the K commodities, a subset $\mathcal{F}$ of these commodities is assumed to be served by the carrier's own train services. In case a demand cannot be delivered by its own train service, the carrier may use the service of a partner (outsource the request) and be charged with a cost of ψ_k. Over the progression of serving the demands, the carrier incurs into certain operation costs including shipping cost, re-sorting cost, and commodity holding cost during the journey. The latter cost arises when the railcars are in idle without being sorted or transferred. In addition, the operator evaluates the risks associated with hazmat transportation when generating trip plans aiming to limit the total public risk and environment impact below given risk thresholds.

2.3.2 Assumptions

In developing the mathematical model, we make the following assumptions:

- The timetable of each service $s \in S$ is fixed at the tactical level and is not a decision variable. That is, for each service s we are aware of its origin, destination, route, en-route stops, capacity and timetable for each leg. Thus, the total cost of selecting and operating services is not incorporated in the model.

- Each demand will be shipped following one of the available itineraries. The demand will not split during transportation.

- All demands and the number of railway cars to be shipped per week are known based on contracts or customers requests. The railway operator has sufficient yard, track and train capacities to satisfy all given demands.

In modeling the risk of hazmat transportation, we mainly considered airborne hazardous materials released to atmosphere in accidents from chlorine, propane, ammonia and other chemical or petroleum products. The effects of airborne hazmats may be measured in terms of exposed population and the size of the total volume of the airborne dispersion with certain threshold of airborne density. As an example, the immediate danger to life and health (IDLH) for propane exposure are 4,200,000 ppm for fatality and 600,000 ppm for injuries. In the developed model, the widely accepted Gaussian Plume Model (GPM) and Box Model (BM) in Arya et al. (1999); Mohan et al. (1995) for air dispersion are used for population and environmental risk calculations. To model airborne dispersion in a rail yard (a terminal), the BM model is used to generate a hemisphere region. The BM model is used to generate a semi-cylinder region if the accident occurs on a track. For the population exposure, it is assumed a rectangular and circle dangerous for track and terminal source, respectively.

Let Q be the release rate (mg/s,m^3/s); u the average downwind speed (m/s); a, b, c, and d be dispersion parameters based on atmospheric stability and $\bar{C}$ the aggregate concentrate level at wind distance point (mg/L,mg/m^3). Frank Pasquill (1983) and Arya et al. (1999) provide the values of dispersion parameters for atmospheric stability class, i.e., A-F. For simplicity, let $n_e(n_i)$ denotes the number of hazmat freights in a train (terminal) along (at the end) direct train-movement link $e \in E^{SM}$ of a certain service. Table 2.1 summarizes the quantitative risk assessment formulas used in the hazmat transportation risk analysis. At certain IDLH level, the operator need to identify a safety distance threshold, and the potential impact volume of the hazmats being transported or in-transit at terminals.

Table 2.1: A summary of GPM and BM for terminal and route.

Public/Environment Risks	***Parameter***	***Approximation function***
$PR_i^{node} = \pi\Phi_i(n_i)\hat{\rho}_i$	*Threshold area*	$\Phi_i(n_i) = \left[\sqrt[b_i+d_i]{\frac{n_i Q}{\pi\ u_i\ a_i\ c_i\ \bar{\mathcal{C}}}} \right]^2 : i \in d_e$
$PR_e^{edge} = 2\Theta_e(n_e)\rho_e q_e$	*Threshold distance*	$\Theta_e(n_e) = \left[\sqrt[b_e+d_e]{\frac{n_e Q}{\pi\ u_e\ a_e\ c_e\ \bar{\mathcal{C}}}} \right] : e \in E^{SM}$
$ER_i^{node} = \frac{1}{2}\frac{4}{3}\pi\chi_i(n_i)\mu_i$	*Impact volume*	$\chi_i(n_i) = \left[\sqrt[b_i+d_i]{\frac{n_i Q}{\pi\ u_i\ a_i\ c_i\ \bar{\mathcal{C}}}} \right]^3 : i \in d_e$
$ER_e^{edge} = \frac{1}{2}\pi\eta_e(n_e)\zeta_e q_e$	*Impact area*	$\eta_e(n_e) = \left[\sqrt[b_e+d_e]{\frac{n_e Q}{\pi\ u_e\ a_e\ c_e\ \bar{\mathcal{C}}}} \right]^2 : e \in E^{SM}$

$PR_i^{node}(PR_e^{edge})$: Population exposure at terminal i (along edge e); $ER_i^{node}(ER_e^{edge})$: Environment damage at terminal i (along edge e). The parameters is function of the hazmat volume being shipped (stored) on the moving edge (terminal).

2.3.3 Mathematical formulation

Solving the multi-time period rail planning problem is to make blocking, train makeup, and railcar freight transportation plans to provide the required services to customers and to minimize total cost including the costs of earliness, tardiness, classification, and holding cost associated with fulfilling all the demands. The risks associated with transporting hazmats are considered by imposing risk threshold constraints. The solution of the problem is to determine for each demand (a) the itinerary that must follow from its origin to destination (b) the sequence of trains that it will be assigned to along the route, and (c) the blocks used to transport it for each train leg along its route (illustrated in Figure 2.1).

In presenting the model, a multi-layer network is followed similar to that in Zhu et al. (2014). The model presented below is formulated considering three layers corresponding to services, blocks and railcars, respectively. An itinerary of a demand is a path in the three-layer network between two IN nodes in the car layer. A block is made of multiple cars. Once it is constructed, it will spend τ_b^H periods on the transfer-delay links at the block origin node, then it will follow a series of attach-block, service section, detach-block, and transfer-delay links. At the block destination node, the block is dismantled at the IN node in the block layer and the shipment will be detached from the block at the corresponding IN node in the car layer. If the node is the destination of a demand, the shipment of the demand is complete. Otherwise, the shipment will continue following the above steps until

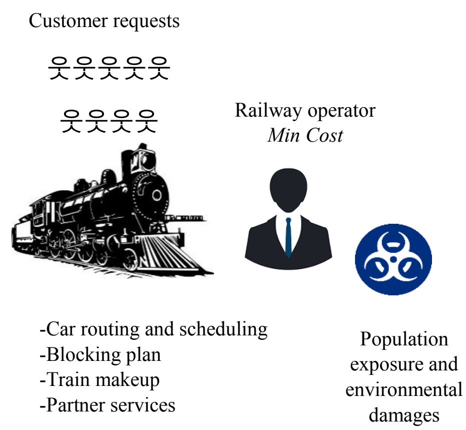


Figure 2.1: Schematic diagram of the HTPs with blocking decisions.

its destination is reached. To route a demand in the car layer, a chain of supporting links in the block layer will be selected with the given train services. For more details of the three-layer network we refer the reader to Zhu et al. (2014).

In the HTPs with blocking decisions, a three multi-layer approach is adapted similar to that in Zhu et al. (2014). However, the main differences between the HTPs with blocking decisions and the freight rail transportation problem studied in Zhu et al. (2014) are the following aspects:

- In the HTPs with blocking decisions, the train services have been decided at tactical level and not subject of change based on the average demands between terminals of the network;
- We explicitly taking into account the risk associated with hazmat transportations by imposing the transport risk thresholds limitations, i.e., population and environmental impact considerations, and, more importantly;
- We explicitly consider the heterogeneous in the customer demands where each request is differentiated by (a) origin and destination (a) available time at their origin, (b)

time window to deliver the commodities at their destination and (c) service time requirements;

Given the above considerations, the sets and parameters are given below.

Sets and Indices

V	Set of railway terminals, index by $v \in V$.
S	Set of available train services, index by $s \in S$.
L_s	Set of sections for service s (a service between two consecutive terminals, but not necessarily adjacent), index by $l \in L_s$.
N	Set of nodes in all layers (terminal at certain time), i.e., service, block, and car layers, index by $i, n \in N$.
N^S	Set of nodes in the service layer, index by $n \in N^S$.
N^B	Set of nodes in the block layer, index by $n \in N^B$.
N^C	Set of nodes in the car layer, index by $n \in N^C$.
E	Set of all links in the virtual network (link set in each layer plus all virtual links), index by $e \in E$.
E^{SM}	Set of links stands for direct train movement from its origin yard at time OUT node to its end yard at time IN node, index by $e \in E^{SM}$.
E^{SR}	Set of links for train stop from yard at time IN node to same yard at time OUT node along its itinerary, index by $e \in E^{SR}$.
B	Set of potential blocks of cars among which the selection should be performed, index by $b \in B$.
$B(v,t)$	Set of potential blocks of cars being constructed at terminal v and time t, index by $b \in B(v,t)$.
L_b	Set of sections for block b (block movement on sections in the service layer), index by $l \in L_b$.
E^{BT}	Set of block transfer links (block-swapping operation) from IN node to OUT node of the transfer yard, index by $e \in E^{BT}$.
E^{BH}	Set of block transfer-delay links at IN nodes (stands for the time the blocking yard assigned at the origin yard), index by $e \in E^{BH}$.
E^{CW}	Set of waiting links (for a demand to avoid congestion) between two consecutive IN nodes, index by $e \in E^{CW}$.
E^{CC}	Set of classification links from IN node to OUT node in the car layer, index by $e \in E^{CC}$.
E^{CH}	Set of holding links between two consecutive OUT nodes in the car layer (waiting for a train service), index by $e \in E^{CH}$.
E^{VBC}	Set of virtual links from IN node of block layer to IN node of car layer (detaching freights from blocks) and from OUT node of car layer to OUT node of block layer (attaching freights to blocks), index by $e \in E^{VBC}$.
E_n^+	Set of links starting from node n, $n \in N$.
E_n^-	Set of links ending at node n, $n \in N$.
K	Set of demands for carload moves, index by $k \in K$.
$\mathcal{F}$	Subset of demands to be served by the carrier's own train services, $\mathcal{F} \subset K$.

Parameters

o_s	Origin node of service s in the service layer, $o_s \in N^S$.
d_s	Destination node of service s in the service layer, $d_s \in N^S$.

$\tau^C_{s,e}$ Schedule cutoff time of service s at edge e, $s \in S, e \in E^{SM}$.
$\tau^A_{s,e}$ Schedule arrival time of service s at edge e, $s \in S, e \in E^{SM}$.
U_s Maximum number of railcars can be hauled by a train service s, $s \in S$.
o_k Origin node of demand k, $o_k \in V$.
d_k Destination node of demand k, $d_k \in V$.
τ^A_k Time when a demand k is available at terminal o_k, $k \in K$.
τ^E_k/τ^L_k Earliness/Lateness time demand k should be delivered at terminal d_k, $k \in K$.
D_k Number of railcars for demand k to be shipped, $k \in K$.
H_k Number of hazmat railcars in demand k to be shipped, $k \in K$.
ψ_k A charge to outsource demand k by a partner (sufficient large number), $k \in K$.
ξ Service level provided by the carrier given by percentage, $\xi \in [0, 1]$.
o_b Origin node of block b in the block layer, $o_b \in N^B$.
d_b End node of block b in the block layer, $d_b \in N^B$.
θ_b Cost to construct block b and perform block-swapping operation, $b \in B$.
U_b Maximum number of cars to be assigned to block b at o_b, $b \in B$.
U_v Maximum number of blocks to be build at terminal v, $v \in V$.
o_e Starting node of link e, $e \in E$.
d_e Ending node of link e, $e \in E$.
q_e Distance of link e, $e \in E^{SM}$.
τ^H_b Time window for block b to be constructed at origin o_b, $b \in B$.
o_l Starting node of section l, $o_l \in N$.
d_l Ending node of section l, $d_l \in N$.
$\tau_{k,e}$ Lateness of demand k shipped along edge e, $e \in E^{VBC}$, $k \in K$.
$C_{e,k}$ Total cost to transport one unit of demand k along link e, $e \in E$.
ρ_e Average population concentration along link e, $e \in E^{SM}$.
$\widehat{\rho_i}$ Average population concentration at the end of link e, $e \in E^{SM}$ and $i \in d_e$.
ζ_e Percentage of environmental sensitive area per distance along link e, $e \in E^{SM}$, $\zeta_e \in [0, 1]$.
μ_i Percentage of environmental sensitive area at the end of link e, $e \in E^{SM}$ and $i \in d_e$, $\mu_e \in [0, 1]$.
R^P/R^E Population exposure/Environment impact threshold.
$\lambda^{s,b}_{e,l} =$ 1 if edge e of service s belongs to section l of block b, 0 otherwise, $s \in S, e \in E^{SM}, b \in B$ & $l \in L_b$.

Variables

$x_{e,k}$ =1 if demand k is moved along link e; 0 otherwise.
$x_{b,k}$ =1 if demand k is assigned to block b; 0 otherwise.
z_k =1 if demand k is outsourced; 0 otherwise.
w_b =1 if block b is constructed; 0 otherwise.
$x_{e,s,k}$ =1 if demand k is moved on link e of service s, $x_{e,s,k} = \sum_{b\in B} \sum_{l \in L_b} \lambda^{s,b}_{e,l} x_{b,k}$.
$x_{s,k}$ Workload of service s with total number of railcars hauled on links it passes, $x_{s,k} = \sum_{e \in E^{SM}} D_k x_{e,s,k}$.

Using the defined parameters and variables presented above, the mathematical programming model for railway hazmat transportation planning problem (HTPs) with blocking decisions is presented below.

$$(P_1) \qquad Z = Min \quad \overbrace{\sum_{b\in B}\theta_b w_b}^{\text{Blocking costs}} + \sum_{k\in K} D_k\Big[\overbrace{\sum_{e\in E} C_{e,k}x_{e,k}}^{\text{Serving costs}} + \overbrace{\psi_k z_k}^{\text{Partner costs}}\Big]$$

$s.t.$

$$\sum_{e\in E_n^+} x_{e,k} - \sum_{e\in E_n^-} x_{e,k} = \begin{cases} 1 - z_k & \forall k, n : n \in o_k \\ z_k - 1 & \forall k, n : n \in d_k \\ 0 & \forall k, n : n \notin o_k \ nor \ d_k \end{cases} \tag{1}$$

$$\tau_{e,k}x_{e,k} \le (1-\xi)\big[\tau_k^L - \tau_k^E\big] \qquad \forall k, e : e \in E^{VBC} and \ d_e \in d_k \tag{2}$$

$$\sum_{k\in K} D_k x_{b,k} \le U_b w_b \qquad \forall b : b \in B \tag{3}$$

$$\sum_{b\in B(v,t)} w_b \le U_v \qquad \forall v, t : v \in V, t \in \{t, .., T\} \tag{4}$$

$$\sum_{k\in K} D_k x_{e,s,k} \le U_s \qquad \forall e, s : e \in E^{SM}, s \in S \tag{5}$$

$$\sum_{s\in S}\sum_{e\in E^{SM}}\left[2\Theta_e\Big(\sum_{k\in K} H_k x_{e,s,k}\Big)\rho_e q_e + \sum_{i\in d_e}\pi\Phi_i\Big(\sum_{k\in K} H_k x_{e,s,k}\Big)\hat{\rho}_i\right] \le R^P \tag{6}$$

$$\sum_{s\in S}\sum_{e\in E^{SM}}\left[\frac{1}{2}\pi\eta_e\Big(\sum_{k\in K} H_k x_{e,s,k}\Big)\zeta_e q_e + \sum_{i\in d_e}\frac{2}{3}\pi\chi_i\Big(\sum_{k\in K} H_k x_{e,s,k}\Big)\mu_i\right] \le R^E \tag{7}$$

$$x_{e,k}, x_{e,s,k}, x_{b,k}, w_b \in \{0,1\} \qquad \forall e \in E, k \in K, s \in S, b \in B \tag{8}$$

The objective function Z in the above model (P_1) is to minimize the total costs including the cost of constructing blocks, cost of waiting for classification and connections, penalty cost for early and late deliveries, and the cost of using outsource services. Constraints (1) are commodity flow conservation constraints for the set of demands fulfilled by the operator. Constraints (2) guarantee the level of service provided by the operator. Constraints (3) link the flow of the demands with the block capacities, if the corresponding blocks have been selected. Constraints (4) are the yard capacities for building blocks at each period, where each block occupies a track for τ_b^H periods at its origin. Constraints (5) are train capacity constraints for the planned services. Constraints (6) and (7) ensure that the total population exposure and environmental risks is lower than given thresholds. The first term in Constraints (6) is the sum of population exposure along the routes, and the second term is that at the yards. Similarly, the first term in Constraints (7) is the sum of the environment damage along the routes and the second term is that at the yards. Constraints (8) are integer variable requirements.

Problem P_1 is a version of Capacitated Multicommodity Network Design (CMND) problems which are NP-hard problems (Magnanti and Wong, 1984; Minoux, 1989). It can be noticed that P_1 can be decomposed to two subproblems. If Constraints (3) are removed or relaxed, the solution of P_1 can be found by solving a block-to-train assignment problem (BAP) and then a freight transportation problem (FTP). Based on this observation, a heuristic algorithm is developed to solve the P_1 model with details of the solution method given in the next section.

2.4 Solution method

In this section, a heuristic solution method to solve the considered train scheduling problem is presented with detail. The solution procedure has two general phases. The first phase has a pre-processing procedure to generate potential car blocks by a blocking generation process. It will also fix certain variables of the model before starting a search process. The non-linear programming model will then be reformulated as an MIP model and solved using a commercial solver. The second phase is a heuristic search procedure, which involves calling a mixed integer programming solution subroutine to solve MIP sub-models iteratively to improve the incumbent solution by prohibiting either the set of blocks or shipments itineraries. The solution of the MIP sub-model should correspond to improved train makeup plans or the shipment itineraries. The search will stop when no significant improvement is found or the total computational time has reached a given limit. More details are presented below.

2.4.1 Preprocessing subroutines

The aim of this subroutines is to reformulate the model and reduce the size of the model in order to be fed and solved using a MIP solver more efficiently. The following blocking generation process is applied in the heuristic given the information of a rail network, the timetables of train services, and the demand requirements.

Blocking generation process

A block is constructed by a set of train cars and a path from the block's origin yard to its destination yard in the rail network. The blocks of train cars are first created and assigned to an available train covering the origin and destination of the block. A block will be assigned to a path if (a) it is feasible to move the block on time considering the entire travel path and (b) the designated train has sufficient capacity to carry the block. The blocking algorithm is to identifies a set of possible paths for all blocks in a timed network with constraints on the network edges reflecting yard capacities. To generate the paths for a block, an extended version of the k-shortest path algorithm is applied to identify several shortest paths to their destination yards. In this work, five short time paths are generated for selection by the local-search based optimization solution method. In addition, the total travel time of a block should be within a certain amount of time as it is a typical practice in railway operations. This procedure is similar to some of those discussed in Ahuja et al. (2007b); Barnhart et al. (2000); Jha et al. (2008); Zhu et al. (2014), with necessary modifications to fit in the optimization method developed in this research.

Variable fixing

The second part of the preprocessing procedure is to fix certain variables before the model is solved by calling optimization subroutines. The variable fixing is based on the following general considerations:

- If the earliest available time of demand at its origin yard is later than the cutoff time for train service, then that demand cannot be assigned to that train. That is, if,

$O_k = \{s \in S, e \in E^{SM} | \tau_k^A > \tau_{s,e}^C\}$, $x_{e,s,k}$ for all shipments and service legs in O_k will be fixed at $x_{e,s,k} = 0$.

- If the capacity of a block is less than the quantity of demand, then this demand cannot be assigned to that block. That is, if, $C_k = \{b \in B | D_k > U_b\}$, $x_{b,k}$ for all shipments and blocks in C_k will be set to 0.

- If a demand cannot arrive before its due date when it is assigned to certain train services, the corresponding variables $x_{e,s,k}$ will be set to 0. Let $D_k = \{s \in S, e \in E^{SM} | \tau_{s,e}^A > \tau_k^L + (1-\xi)[\tau_k^L - \tau_k^E]\}$ be a set of services that a commodity k cannot be assigned in a solution due to violation of service level constraints.

The above preprocessing subroutines may reduce the size of the model by two to three orders of magnitude.

Function linearization

To simplify computation, in the third part of the preprocessing, piecewise linear functions were used to substitute the nonlinear hazmat risk functions in GPM and BM models. The resulting optimization model can be then solved using popular MIP commercial software without invoking the search for local or global optimal solutions of a nonlinear problem. The details of the linearization process is presented below.

Let $n_{s,e}$ be the number of hazmat freights along the direct train-moving link $e \in E^{SM}$ of train service s. Three intervals are used in the piecewise linearization method to balance between quality of solution and computation time. Let also $p \in \{1, 2, 3\}$ be the set of intervals in the piecewise linear function. For each interval p, let M_p^+ and M_p^- be the lower and upper bounds of $n_{s,e}$, respectively. For modeling purpose, the following parameters and auxiliary variables are introduced:

Parameters

$\vartheta_{s,e,p}$	Slope of the severe distance along the direct train-moving link $e \in E^{SM}$ of service s given that the number of hazmat within the interval p; $n_{s,e} \in (M_p^-, M_p^+]$.
$\gamma_{s,e,p}$	Y-intercept of the severe distance along the direct train-moving link $e \in E^{SM}$ of service s given that the number of hazmat within the interval p; $n_{s,e} \in (M_p^-, M_p^+]$.
$\varepsilon_{s,e,i,p}$	Slope of the severe area through terminal $i \in d_e$ at the end of the direct train-moving link $e \in E^{SM}$ of service s given that the number of hazmat within the interval p; $n_{s,e} \in (M_p^-, M_p^+]$.
$\Upsilon_{s,e,p}$	Slope of the impact area along the direct train-moving link $e \in E^{SM}$ of service s given that $n_{s,e} \in (M_p^-, M_p^+]$.
$\nu_{s,e,i,p}$	Slope of the impact volume through terminal $i \in d_e$ at the end of the direct train-moving link $e \in E^{SM}$ of service s given that the number of hazmat within the intervals p; $n_{s,e} \in (M_p^-, M_p^+]$.

Auxiliary variables

$W_{s,e,p}$	Binary variable =1 if the volume of hazmat freights along the direct train-moving link $e \in E^{SM}$ of service s is within interval p, 0 otherwise.
$V_{s,e,p}$	Integer variable = total number of hazmat freights along direct train-moving link $e \in E^{SM}$ of service s and the value within range p.

Therefore, Constraints (6),(7) can be re-written as follows:

$$\sum_{s\in S}\sum_{e\in E^{SM}}\sum_{p\in P}\left[2\left[\vartheta_{s,e,p}V_{s,e,p}+\gamma_{s,e,p}W_{s,e,p}\right]\rho_e q_e+\sum_{i\in d_e}\pi\varepsilon_{s,e,i,p}V_{s,e,p}\hat{\rho}_i\right]\leq R^P \tag{9}$$

$$\sum_{s\in S}\sum_{e\in E^{SM}}\sum_{p\in P}V_{e,p}\left[\frac{1}{2}\pi\Upsilon_{s,e,p}\zeta_e d_e+\sum_{i\in d_e}\frac{2}{3}\pi\nu_{s,e,i,p}\mu_i\right]\leq R^E \tag{10}$$

Additional constraints are presented below:

$$\sum_{p\in P}W_{s,e,p}=1 \qquad \forall s\in S, e\in E^{SM} \tag{11}$$

$$\sum_{p\in P}M_p^-W_{s,e,p}\leq\sum_{p\in P}V_{s,e,p}\leq\sum_{p\in P}M_p^+W_{s,e,p} \qquad \forall s\in S, e\in E^{SM} \tag{12}$$

$$\sum_{p\in P}V_{s,e,p}=\sum_{k\in K}\sum_{b\in B}\sum_{l\in L_b}\lambda_{e,l}^{s,b}H_k x_{b,k} \qquad \forall s\in S, e\in E^{SM} \tag{13}$$

$$W_{s,e,p}\in\{0,1\} \qquad \forall s,e,p \tag{14}$$

$$V_{s,e,p}\in R_+ \qquad \forall s,e,p \tag{15}$$

Figure 2.2 shows a piecewise linear function to approximate the severe distance along

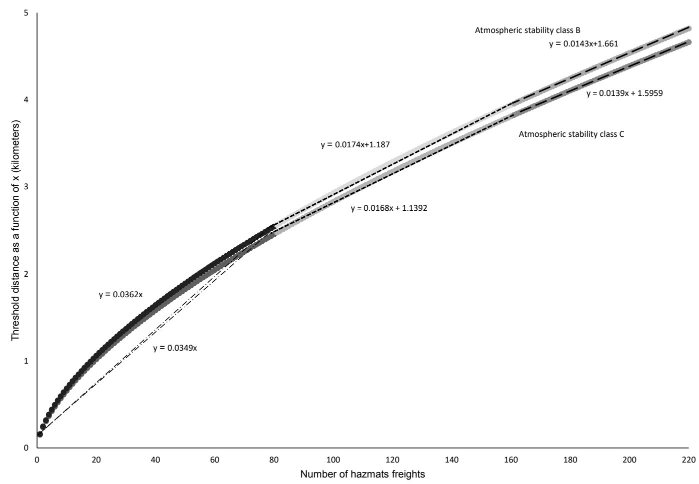


Figure 2.2: Piecewise linearization for threshold distance.

a railway track if there is a train derailment and a hazmat spill, a train service s_a with atmospheric stability class B (top) and s_b with atmospheric stability class C (bottom). Analogously, Figure 2.3 depicts a piecewise linear function to approximate the severe zone if there is a hazmat spill in a rail yard, through terminal i_a with atmospheric stability class B (top) and i_b with atmospheric stability class C (bottom). It could be used by a railway operator to conduct a judicious assessment of the operation costs and population exposure to hazmat transportation. As mentioned earlier, different customers have different service requirements. Some customers require service with fixed due dates, whereas other customers are more flexible. It may be feasible to delay a previously scheduled hazmat shipment from a train service s_a to s_b in a favor of other shipments to take advantage of time varying-nature of population density and/or weather conditions. For instance, if the railway operator delay (or shipped earlier) a single hazmat commodity from a train service s_a with hazmat volume within range p_3 to train service s_b within range p_3, the severe zone can be reduced by 0.0655 kilometer.

Similarly, Figure 2.3 could be also used by the decision maker to reroute the hazmat freights from terminals with high population density or those terminals with atmospheric class A or B. For instance, the operator may decide to release a demand from yard through the earliest available train if the population exposure from holding the demand at that terminal exceeding a given threshold. That is, the heterogeneity of traffic has to be the main criteria to build trip plans. However, it is relatively challenged when the differentiate occurred among different shipments that are consolidated within the same block (Kwon et al., 1998).

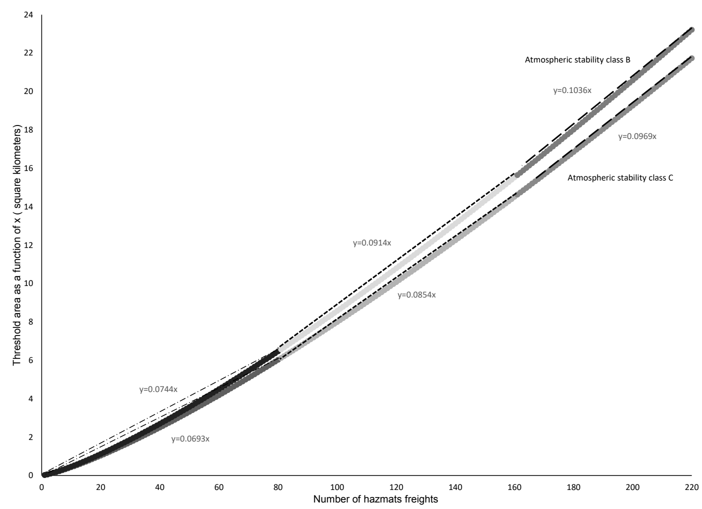


Figure 2.3: Piecewise linearization for threshold area.

After applying the block generation algorithm, variable fixing, and piecewise linearization process as discussed above, the original optimization model P_1 is reduced to the following linear integer programming (IP) model, P_2:

$$(P_2) \qquad Z = Min \sum_{b \in B} \theta_b w_b + \sum_{k \in K} D_k \Big[\sum_{e \in E} C_{e,k} x_{e,k} + \psi_k z_k \Big]$$

$s.t.$

$$\sum_{e \in E_n^+} x_{e,k} - \sum_{e \in E_n^-} x_{e,k} = \begin{cases} 1 - z_k & \forall k, n : n \in o_k \\ z_k - 1 & \forall k, n : n \in d_k \\ 0 & \forall k, n : n \notin o_k \ nor \ d_k \end{cases}$$

$$\tau_{e,k}x_{e,k} \leq (1-\xi)[\tau_k^L - \tau_k^E] \qquad \forall k,e : e \in E^{VBC} and\ d_e \in d_k$$

$$\sum_{k\in K} D_k x_{b,k} \leq U_b w_b \qquad \forall b : b \in B$$

$$\sum_{b\in B(v,t)} w_b \leq U_v \qquad \forall v,t : v \in V, t \in \{t,..,T\}$$

$$\sum_{k\in K} D_k x_{e,s,k} \leq U_s \qquad \forall e,s : e \in E^{SM}, s \in S$$

$$\sum_{s\in S}\sum_{e\in E^{SM}}\sum_{p\in P}\left[2\left[\vartheta_{s,e,p}V_{s,e,p} + \gamma_{s,e,p}W_{s,e,p}\right]\rho_e q_e + \sum_{i\in d_e}\pi\varepsilon_{s,e,i,p}V_{s,e,p}\hat{\rho}_i\right] \leq R^P$$

$$\sum_{s\in S}\sum_{e\in E^{SM}}\sum_{p\in P} V_{e,p}\left[\frac{1}{2}\pi\Upsilon_{s,e,p}\zeta_e q_e + \sum_{i\in d_e}\frac{2}{3}\pi\nu_{s,e,i,p}\mu_i\right] \leq R^E$$

$$\sum_{p\in P} W_{s,e,p} = 1 \qquad \forall s,e : s \in S, e \in E^{SM}$$

$$\sum_{p\in P} M_p^- W_{s,e,p} \leq \sum_{p\in P} V_{s,e,p} \leq \sum_{p\in P} M_p^+ W_{s,e,p} \qquad \forall s,e : s \in S, e \in E^{SM}$$

$$\sum_{p\in P} V_{s,e,p} = \sum_{k\in K}\sum_{b\in B}\sum_{l\in L_b}\lambda_{e,l}^{s,b} H_k x_{b,k} \qquad \forall s,e : s \in S, e \in E^{SM}$$

$$W_{s,e,p} \in \{0,1\} \qquad \forall s,e,p$$

$$V_{s,e,p} \in Z_+ \qquad \forall s,e,p$$

$$x_{e,k}, x_{e,s,k}, x_{b,k}, w_b \in \{0,1\} \qquad \forall e \in E, k \in K, s \in S, b \in B$$

2.4.2 Heuristic search

During the last decade, the concept of combining mathematical programming and metaheuristic methods has gained attention within the academic literature. In this chapter, a matheuristic method is presented that combines mathematical programming with flexibility of local search heuristics. A simple tabu search was adopted to improve the performance of local search by prohibiting previously-visited solutions. A non-tabu move is accepted only if the new solution is better than the best solution obtained so far. One can find matheuristic attempting to solve railway planning and scheduling problems in Anghinolfi et al. (2011); Zhu et al. (2014), and vehicle routing and transportation logistics in Doerner and Schmid (2010), among others. Surveys on matheuristics can be found in Archetti and Speranza (2014); Boschetti et al. (2009). Matheuristics have been demonstrated to be a promising solution method to solve a large scale combinatorial problem in order to explore the solution space more efficiently.

Problem (P_2) is a generalized assignment problem which involves two main nested assignment decisions; the assignment of blocks to train services, through w_b variables, and the assignment of commodities to blocks according to the selected blocking paths, through $x_{b,k}$. The MIP heuristic is designed to account the hierarchy nature of the considered problem, railcars are accumulated to build blocks and blocks grouped to form trains, through the destroy operators at either the block or shipment layer. The first heuristic focuses on the train makeup problem by fixing the subset of the blocking plans and then the restricted train makeup and freight transportation problems are solved. The other heuristic attempts to fix the subset of the freight itineraries and then train makeup and restricted freight transportation problems are tackled. It has two main subroutines: constructing the initial feasible solution and then reoptimizing the blocking plans and shipment itineraries.

A feasible solution of Problem (P_1) is obtained by giving a fixed time limit to the MIP solver to solve the linearized model of P_1. Then, the current solution is iteratively improved by prohibiting either a set of blocking plans or shipment itineraries. This has been done to discourage the search from coming back to previously visited solutions. The forbidden moves are stored in a tabu list and the best non-tabu move is chosen to obtain the best local minimum. A non-tabu move is accepted only if the new solution is better than the best solution obtained so far. The above step is repeated until a given amount of CPU time is reached or a pre-defined number of non-improved local searches is achieved. A detail approach is given below:

The block MIP heuristic

The block MIP heuristic (BH) focuses on the w_b binary variables, as they determine the highest level of assignment decisions and the dimension of solution space. It consists of obtaining the best routing and scheduling for freight of cars when a subset of the blocking plans is fixed. Let $R_r(b)$ be a set of all blocking plans that is banned in an iteration r, that is $w_b = 0$ for all blocking plans in set R_r at iteration r. The heuristic iteratively solves a sequence of the MIP sub-problems of the (P_2) model with the subset of w_b binary variables fixed as explained earlier.

The method then identifies the q worse blocks with some randomness to be removed from a solution at an iteration. The randomness has been introduced in the previous step to avoid situations where the same block paths are entering and leaving the set of forbidden solutions too frequently. The BH method starts with an empty set in $R_r(b)$. Then, at any iteration r, the subset of $w_b \backslash R_{r-1}(b)$ to be investigated is determined, for each block, as follows:

- By inserting in $R_r(b^*)$ (i.e., fixing the lower and upper bound to 0) the variable w_{b^*} $\backslash R_{r-1}(b)$ such that $w_{b^*} = 1$ at iteration $r-1$ and $b^* = y^c|L|$, where $|L|$ denotes a set of blocks sorted (descending) based on their value in the objective function, y is a random number from interval $[0, 1)$, and c is a deterministic parameter ($\geq$1) that introduces some randomness.

The shipment MIP heuristic

The shipment MIP heuristic (SH) focuses on the $x_{e,s,k}$ binary variables, as they determine the lowest level assignment decisions. It consists of obtaining the best routing and scheduling for freight of cars when a set of commodities itineraries are fixed. Note that the number of lower level assignment decisions is much larger than the highest level assignment variables. The method identifies q worse shipments to be removed from a solution at an iteration. In this way, it supposes to guide the solver on the most convenient assignment decisions to be reset into 1 by limiting the solution space. The heuristic iteratively solves a sequence of the MIP sub-problems of the (P_2) model with the subset of $x_{e,s,k}$ binary variables fixed as explained earlier. The SH method starts with an empty set in $R_r(e, s, k)$. Then, at any iteration r, the subset of $x_{e,s,k} \backslash R_{r-1}(e, s, k)$ to be investigated is determined, for each shipment, as follows:

- By inserting in $R_r(e, s, k^*)$ (i.e., fixing the lower and upper bound to 0) the variable $x_{e,s,k^*} \backslash R_{r-1}(e, s, k)$ such that $x_{e,s,k^*} = 1$ at iteration $r-1$ and $k^* = y^c|L|$, where $|L|$ denotes a set of shipments sorted (descending) based on their values in the objective function.

Summary of the solution method

In both methods, the partially fixed MIP sub-problems (P_2) are solved by limiting both the computation time and number of nodes in the MIP solver at each iteration. The procedure continues until a given amount of CPU time is reached or a predefined number of non-improved local searches is achieved, which come first. The whole solution procedure was tested using a number of numerical examples of the HTPs discussed in the next section. In summary, the steps of the solution procedure are given in Algorithm 1.

Algorithm 1 Blocking/Shipment MIP heuristic.

Read data: the network information, list of request requirements, and list of planned train services;
Phase 1: Preprocessing subroutines (Section 2.4.1)
Step 1.1: Blocking generation process (Subsection 2.4.1);
Generate all possible blocking plans by applying *k-shortest paths* for each candidate block b;
Determine the services for block along its section(s) $\lambda_{e,l}^{s,b}$;
Obtain the subset of services/blocks for each request k;
Fix a subset of decision variables (Subsection 2.4.1);
Step 1.2: Reformulate the model from NIP into IP (linearized version of P_1) (Subsection 2.4.1);
Phase 2: Heuristic phase (Section 2.4.2)
Step 2.1: Find a feasible solution by solving the linearized model of P_1;
Step 2.2: Apply local search procedure by destroying a subset of blocking plans (Subsection 2.4.2) or shipment itineraries (Subsection 2.4.2) with some randomness;
Obtain the best blocking plan and freight transportation decisions

---

We also propose alternative mathematical formulation model and heuristic method to solve real-size problem instances in Appendix A.

2.5 Computational experiments

A series of computational experiments were conducted to analyze the performance of the MIP heuristics given in section 2.5.3. Both the pre-analysis procedure and the solution approaches were implemented under the same programming language and computational environment, in particular, the MIP optimization problem was solved using Cplex v.12.7.1

and the ILOG concert technology for constructing the model in C++. All instances were run on a DELL laptop with an Intel(R) Core(TM) i7-6700HQ CPU 2.60GHz and 16.0 GB under Window 10 environment.

2.5.1 Random instances

Four set of scenarios were designed, detailed in Table 2.2, based on different dimensions of railway network and number of train leg services. Set S includes small instances with only 7 nodes, 13 edges, and 27 train legs. Set M is the medium set, and the instances have 11 nodes, 21 edges, and 32 train legs. Set $L1$ and $L2$ are the large sets with 15 nodes, and 33 edges. In the set $L2$ has 40 additional train leg services than set $L1$, which are large and difficult to be solved. The consider rail network for set S ($L1$) and M ($L2$) is shown in Figure 2.4 (Figure 2.6) and Figure 2.5 (Figure 2.7), respectively.

Table 2.2: Dimensions of the four scenarios.

Scenario	Number of nodes	Number of edges	Number of train legs
S	7	13	27
M	11	21	32
$L1$	15	33	57
$L2$	15	33	97

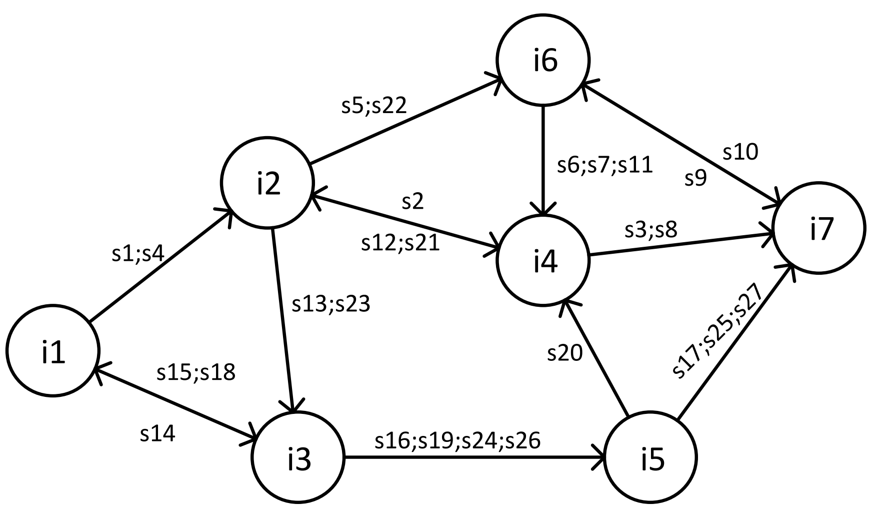


Figure 2.4: A railway network in set S.

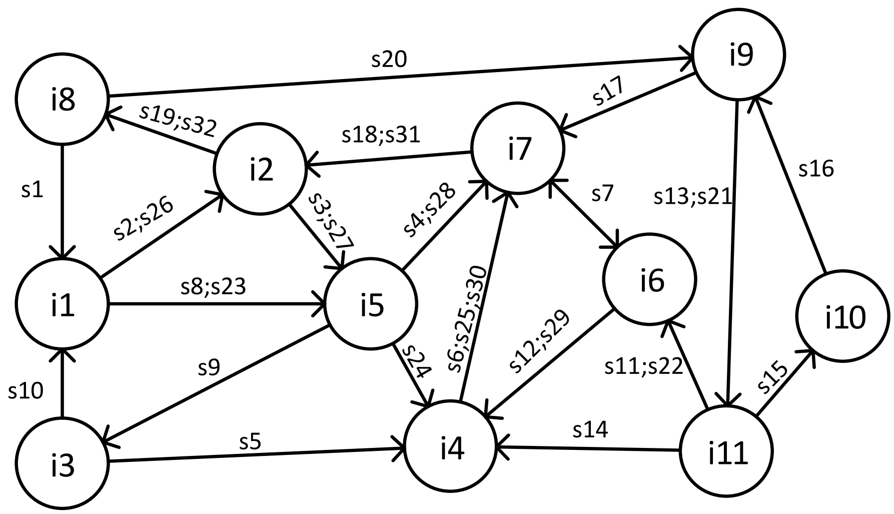


Figure 2.5: A railway network in set M.

For each scenario, six groups of instances were generated, denoted by A-F. Group A includes the base instances, default parameters. Group B contains instances with lowest demand quantities, whereas the instances in group C have the highest demand quantities. Instances in group D have loose train capacities, whereas the compact services are generated in group E. Group F consists of instances with the highest risk parameters, atmospheric class range from A to D. For each combination of railway network dimension and group, two instances are generated with increasing number of requests to roughly partition the car flow density. Table 2.3 and Table 2.4 report specific parameters of the group of instances in S/M and $L1/L2$ set including the demand quantity, train capacity, atmospheric class, number O-Ds and number of blocking plans, respectively.

Table 2.3: Characteristics of the groups of S/M instances.

Group	Demand rate	Train capacity	Atmospheric class	Number of O-Ds	Number of block paths
A	U[5,15]	U[60,110]	U[1,6]	42/80	175/242
B	U[3,10]	U[60,110]	U[1,6]	42/94	201/495
C	U[10,15]	U[60,110]	U[1,6]	42/71	175/418
D	U[5,15]	U[80,180]	U[1,6]	42/84	175/370
E	U[5,15]	U[50,80]	U[1,6]	42/80	175/242
F	U[5,15]	U[60,110]	U[1,4]	42/80	175/242

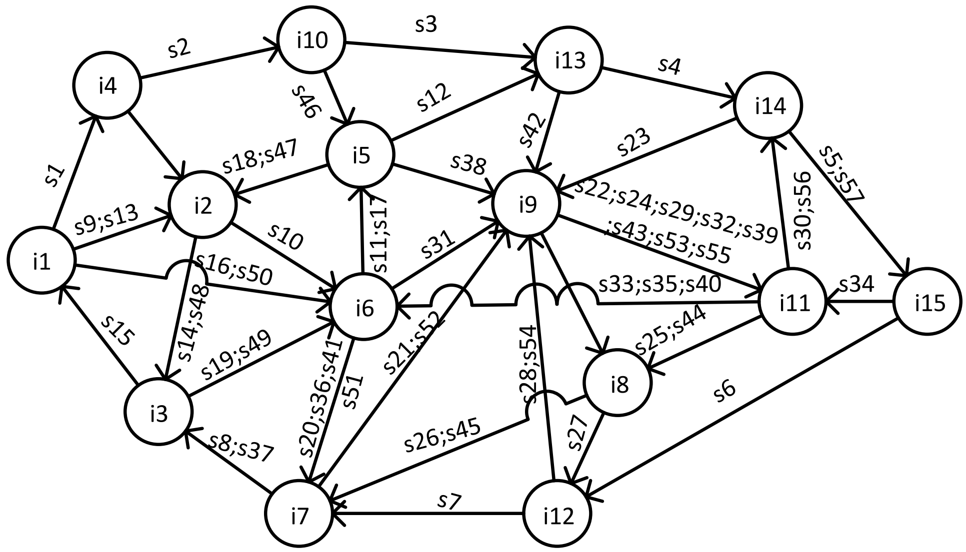


Figure 2.6: A railway network in set $L1$.

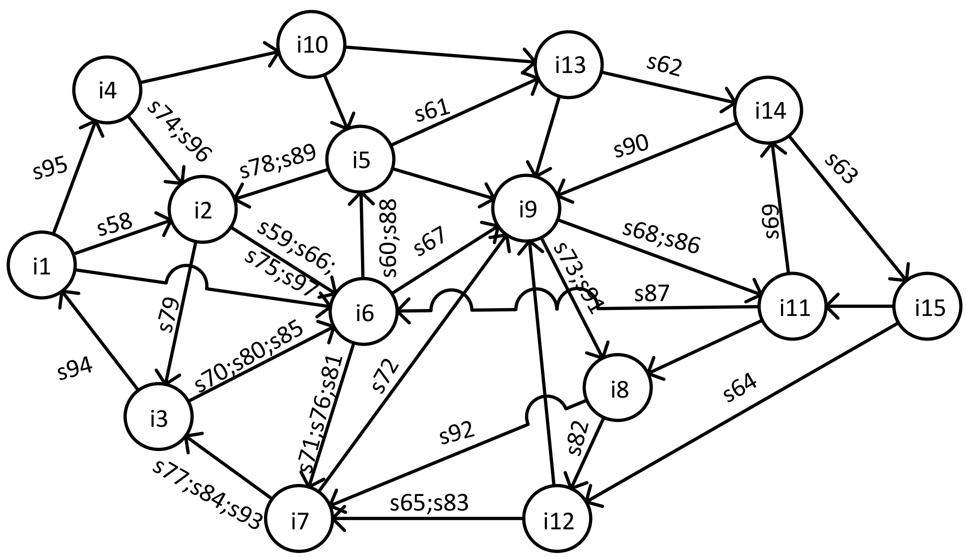


Figure 2.7: A railway network in set $L2$.

Table 2.4: Characteristics of the groups of $L1/L2$ instances.

Group	Demand rate	Train capacity	Atmospheric class	Number of O-Ds	Number of block paths
A	U[5,15]	U[150,180]	U[1,6]	184/199	1912/2470
B	U[3,10]	U[150,180]	U[1,6]	172/199	1212/1905
C	U[10,15]	U[150,180]	U[1,6]	176/171	1365/1754
D	U[5,15]	U[160,190]	U[1,6]	181/198	2285/2197
E	U[5,15]	U[120,160]	U[1,6]	181/197	1359/1842
F	U[5,15]	U[150,180]	U[1,4]	184/199	1912/2470

All experimental tests have been randomly generated problem instances taking into account some realistic data, deriving from the North American rail system when available, relevant to the railway network and train timetable, risk parameters, and randomly generating the requests. Some of the parameters are adapted based on the RAS 2011 Problem Solving Competition and Verma et al. (2011). The train routes and timetables were designed to satisfy each O-D request in the instance. The train journeys are supposed to be the same on each day, the available paths for each block range between 1 and 22 and each train covers between 1 and 4 railway edges. It is assumed that the shipments must be shipped to their destination from their origin in 4-11 days. The origin and destination terminals of each request were generated from the discrete uniform distribution $U[1, n]$, where n is the number of the terminals in the instance; the available time was chosen as $\tau_k^A \sim U[0, 2.5]$ (expressed in days), the earliest due time as $\tau_k^E \sim \tau_k^A + U[4, 7]$ and the due date as $\tau_k^L \sim U[4.5, 11]$. A \$0.875 was estimated to move a regular railcar one mile, whereas a hazmat railcar was assumed to be \$1.163. The classification cost (dollar per railcar) was obtained from a $U[50, 70]$. The capacity of each block was obtained from a discrete uniform distribution $U[30, 65]$; the block swap cost in dollar per block was selected from a $U[30, 70]$; the block constructing cost was chosen from a $U[3.5k, 4.5k]$. The maximum number of block-swaps was assumed to be 3 swaps per block. Finally, the atmospheric, population concentration parameters and environmental sensitive factors are generated randomly for each train service and terminal in the instance.

For the solution provided by Cplex and proposed heuristics, 1 hour time limit was given for instances in group $L2$, whereas instances in groups S, M, and $L1$ were limited to half-hour to be solved. The node limit for the branch-and-cut investigation was fixed to 1000 nodes with variable less than 30000 and single node for instances in group $L1$ and $L2$. Cplex Solver stops when an optimal solution is proven or the maximum computational time is reached, whereas as the MIP heuristics terminate at 4 non-improved local searches or when the time allocated is exceeded.

2.5.2 Small instances

In the this section we solved a small instance, railway network consists of 7 nodes and 27 service legs, in details. Table 2.5 gives the characteristics of each request with regards to origin-destination, quantity of commodities including hazmat freight, time when request available at its origin and delivery time windows. We design 10 train services where each service consists of 2-3 train legs.

Table 2.5: Characteristics of the shipments.

K	$o_k - d_k$	$D_k(H_k)$	τ_k^A	$[\tau_k^E, \tau_k^L]$
k_1	5−7	9(2)	2.82	[3.27, 3.61]
k_2	1−2	10(3)	0.20	[4.40, 4.86]
k_3	7−1	9(3)	1.08	[5.66, 6.26]
k_4	7−4	9(2)	1.08	[2.90, 3.20]
k_5	4−2	8(1)	3.05	[4.40, 4.86]
k_6	6−5	10(3)	1.82	[5.44, 6.02]
k_7	5−7	9(3)	2.82	[3.59, 3.97]
k_8	5−6	8(1)	2.82	[4.28, 4.74]
k_9	2−7	7(1)	1.27	[3.27, 3.61]
k_{10}	7−6	8(2)	1.08	[1.63, 1.81]
k_{11}	3−7	9(2)	1.37	[3.27, 3.61]
k_{12}	2−3	8(2)	1.27	[1.74, 1.92]
k_{13}	6−3	8(2)	1.82	[4.95, 5.47]
k_{14}	3−7	8(1)	1.37	[3.59, 3.97]
k_{15}	1−2	9(2)	0.20	[0.85, 0.93]
k_{16}	4−5	8(2)	3.05	[5.44, 6.02]
k_{17}	2−6	9(3)	1.27	[2.04, 2.26]
k_{18}	2−1	8(2)	1.27	[5.66, 6.26]
k_{19}	7−4	9(2)	1.08	[2.38, 2.63]
k_{20}	4−2	10(3)	3.05	[4.40, 4.86]
k_{21}	1−5	7(1)	0.20	[2.01, 2.23]

K	$o_k - d_k$	$D_k(H_k)$	τ_k^A	$[\tau_k^E, \tau_k^L]$
k_{22}	5−4	9(2)	3.28	[3.72, 4.12]
k_{23}	4−2	8(2)	3.05	[4.40, 4.86]
k_{24}	1−5	9(3)	0.20	[2.01, 2.23]
k_{25}	3−2	8(1)	1.37	[4.40, 4.86]
k_{26}	4−1	8(1)	3.05	[5.66, 6.26]
k_{27}	2−6	7(1)	1.27	[2.04, 2.26]
k_{28}	2−5	8(2)	1.27	[2.68, 2.96]
k_{29}	2−4	10(3)	1.27	[6.17, 6.81]
k_{30}	4−6	8(1)	2.93	[4.28, 4.74]
k_{31}	7−3	8(2)	1.08	[4.95, 5.47]
k_{32}	7−6	7(1)	1.08	[1.63, 1.81]
k_{33}	4−6	12(5)	2.93	[5.06, 5.60]
k_{34}	7−6	8(2)	1.08	[1.63, 1.81]
k_{35}	7−7	9(2)	0.17	[3.59, 3.97]
k_{36}	2−5	8(2)	1.27	[5.44, 6.02]
k_{37}	3−1	8(2)	5.31	[5.66, 6.26]
k_{38}	3−5	9(3)	1.37	[2.01, 2.23]
k_{39}	5−2	9(3)	3.28	[4.40, 4.86]
k_{40}	1−4	8(1)	0.20	[2.90, 3.20]
k_{41}	1−6	7(1)	0.20	[5.06, 5.60]
k_{42}	2−5	10(3)	1.27	[5.44, 6.02]

Table 2.6 gives the operational characteristic of each train service with regards to route, schedule, capacity and atmospheric class. These train services have been designed in advance such that each request has a least one feasible itinerary with respect to service requirements, i.e., available time τ_k^A and delivery time windows $\tau_k^T \in [\tau_k^E, \tau_k^L]$. Figure 2.8 sketches the train movement over time across railway network. Each line in Figure 2.8 represents a unique train service composed of set of train segments. The set of train segments forms the backbone of the blocking plan and freight transportation problem.

Table 2.7 gives information of the candidate blocks including their origin and capacity. Note that the destination of blocks are undefined. It is common approach to define the blocking plan in advance based on the forecast of future demands between major cities.

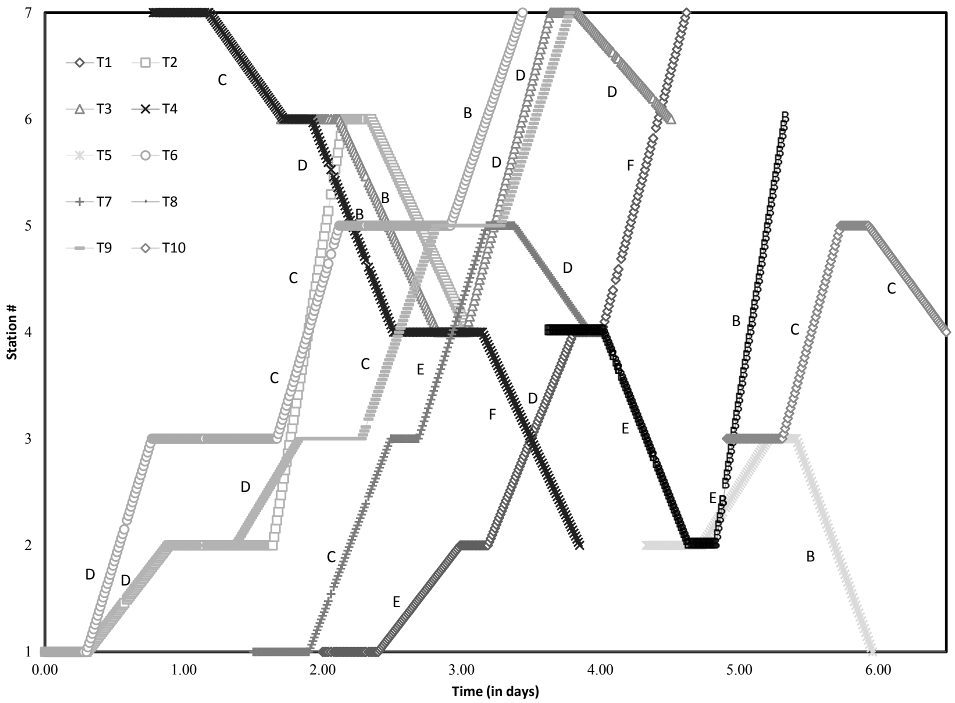


Figure 2.8: A timetable of the set of plan services.

Such strategy limits the benefit to adjust the operating plan when the transport demand fluctuates over time. Since we do not defined the destination of the block in the blocking plan, we create more flexibility in the way trip plans are generated. Such flexibility increases in terms of routing and scheduling options, where block of cars can be routed to various paths through rail network, temporary stored at yards and pulled on different train services.

We fed all information of the considered instance into our algorithm. The problem was solved in few seconds. The solution of problem gives a complete information of the blocking policy, train makeup as well as freight transportation plans. Table 2.8 gives information regrading the blocking plan, whereas Table 2.9 and 2.10 describes the itinerary of each request including the blocking path it assigned along the path. The algorithm constructs 14 blocks out of 30 candidate blocks. Figure 2.9 shows the block movements over train segments. Each section of block can be treated as unique service with regards to its route,

Table 2.6: Timetable for each direct train service and the atmospheric class.

Service	*Itinerary*	τ_l^O			τ_l^C			τ_l^D			τ_l^A		
-	-	s_1	s_2	s_3	s_1	s_2	s_3	s_1	s_2	s_3	s_1	s_2	s_3
T_1	$i_1 \xrightarrow[E]{l_1(82)} i_2 \xrightarrow[D]{l_2(87)} i_4 \xrightarrow[F]{l_3(109)} i_7$	2.00	2.89	3.71	2.29	3.09	3.91	2.40	3.19	4.01	2.99	3.81	4.62
T_2	$i_1 \xrightarrow[D]{l_4(79)} i_2 \xrightarrow[C]{l_5(74)} i_6 \xrightarrow[B]{l_6(67)} i_4$	0.00	1.24	2.04	0.20	1.54	2.25	0.30	1.64	2.35	0.89	2.15	3.05
T_3	$i_6 \xrightarrow[B]{l_7(109)} i_4 \xrightarrow[D]{l_8(106)} i_7 \xrightarrow[D]{l_9(82)} i_6$	1.70	2.73	3.54	2.00	2.93	3.74	2.12	3.03	3.84	2.83	3.64	4.51
T_4	$i_7 \xrightarrow[C]{l_{10}(63)} i_6 \xrightarrow[D]{l_{11}(95)} i_4 \xrightarrow[F]{l_{12}(67)} i_2$	0.78	1.62	2.75	1.08	1.82	3.05	1.18	1.92	3.15	1.72	2.50	3.85
T_5	$i_2 \xrightarrow[E]{l_{13}(76)} i_3 \xrightarrow[B]{l_{14}(62)} i_1$	4.33	5.11	-	4.63	5.31	-	4.73	5.41	-	5.21	5.96	-
T_6	$i_1 \xrightarrow[D]{l_{15}(98)} i_3 \xrightarrow[C]{l_{16}(76)} i_5 \xrightarrow[D]{l_{17}(101)} i_7$	0.00	1.07	2.52	0.20	1.37	2.82	0.30	1.67	2.92	0.77	2.12	3.44
T_7	$i_1 \xrightarrow[C]{l_{18}(106)} i_3 \xrightarrow[E]{l_{19}(81)} i_5 \xrightarrow[D]{l_{20}(108)} i_4$	1.50	2.39	3.08	1.80	2.59	3.28	1.90	2.69	3.38	2.49	3.18	3.92
T_8	$i_4 \xrightarrow[E]{l_{21}(95)} i_2 \xrightarrow[B]{l_{22}(66)} i_6$	3.62	4.53	-	3.92	4.73	-	4.01	4.83	-	4.63	5.33	-
T_9	$i_2 \xrightarrow[D]{l_{23}(68)} i_3 \xrightarrow[C]{l_{24}(80)} i_5 \xrightarrow[D]{l_{25}(74)} i_7$	0.97	1.88	2.88	1.27	2.18	3.18	1.37	2.27	3.28	1.83	2.82	3.78
T_{10}	$i_3 \xrightarrow[C]{l_{26}(103)} i_5 \xrightarrow[C]{l_{27}(69)} i_4$	4.91	5.63	-	5.21	5.83	-	5.31	5.93	-	5.73	6.49	-

Table 2.7: Characteristics of the blocks.

Block#	$o_b - d_b$	U_b	*Block#*	$o_b - d_b$	U_b
b_1	$4-\times$	44	b_2	$5-\times$	47
b_3	$7-\times$	52	b_4	$4-\times$	46
b_5	$2-\times$	45	b_6	$3-\times$	40
b_7	$6-\times$	45	b_8	$3-\times$	57
b_9	$4-\times$	41	b_{10}	$3-\times$	54
b_{11}	$6-\times$	43	b_{12}	$7-\times$	45
b_{13}	$1-\times$	60	b_{14}	$5-\times$	58
b_{15}	$2-\times$	58	b_{16}	$4-\times$	55
b_{17}	$3-\times$	48	b_{18}	$2-\times$	52
b_{19}	$1-\times$	58	b_{20}	$5-\times$	58
b_{21}	$7-\times$	57	b_{22}	$4-\times$	56
b_{23}	$3-\times$	44	b_{24}	$3-\times$	43
b_{25}	$1-\times$	44	b_{26}	$4-\times$	43
b_{27}	$4-\times$	40	b_{28}	$3-\times$	55
b_{29}	$6-\times$	43	b_{30}	$1-\times$	43

Table 2.8: Train makeup plan (block-to-train assignment decisions).

Block	*Itinerary*	*Block*	*Itinerary*
b_1	$i_4 \xrightarrow{l_{21}} i_2^* \xrightarrow{l_{13}} i_3^* \xrightarrow{l_{26}} i_5$	b_{17}	$i_3 \xrightarrow{l_{19}} i_5 \xrightarrow{l_{20}} i_4$
b_6	$i_3 \xrightarrow{l_{16}} i_5^* \xrightarrow{l_{25}} i_7$	b_{18}	$i_2 \xrightarrow{l_{23}} i_3 \xrightarrow{l_{24}} i_5$
b_7	$i_6 \xrightarrow{l_7} i_4 \xrightarrow{l_8} i_7$	b_{19}	$i_1 \xrightarrow{l_4} i_2^* \xrightarrow{l_{23}} i_3^* \xrightarrow{l_{19}} i_5$
b_8	$i_3 \xrightarrow{l_{16}} i_5 \xrightarrow{l_{17}} i_7^* \xrightarrow{l_9} i_6$	b_{21}	$i_7 \xrightarrow{l_{10}} i_6 \xrightarrow{l_{11}} i_4 \xrightarrow{l_{12}} i_2$
b_{12}	$i_7 \xrightarrow{l_{10}} i_6 \xrightarrow{l_{11}} i_4 \xrightarrow{l_{12}} i_2$	b_{25}	$i_1 \xrightarrow{l_4} i_2 \xrightarrow{l_5} i_6 \xrightarrow{l_6} i_4$
b_{13}	$i_1 \xrightarrow{l_{15}} i_3 \xrightarrow{l_{16}} i_5$	b_{28}	$i_3 \xrightarrow{l_{19}} i_5 \xrightarrow{l_{20}} i_4^* \xrightarrow{l_{21}} i_2 \xrightarrow{l_{22}} i_6$
b_{15}	$i_2 \xrightarrow{l_{13}} i_3 \xrightarrow{l_{14}} i_1$	b_{29}	$i_6 \xrightarrow{l_{11}} i_4 \xrightarrow{l_{12}} i_2^* \xrightarrow{l_{13}} i_3 \xrightarrow{l_{14}} i_1$

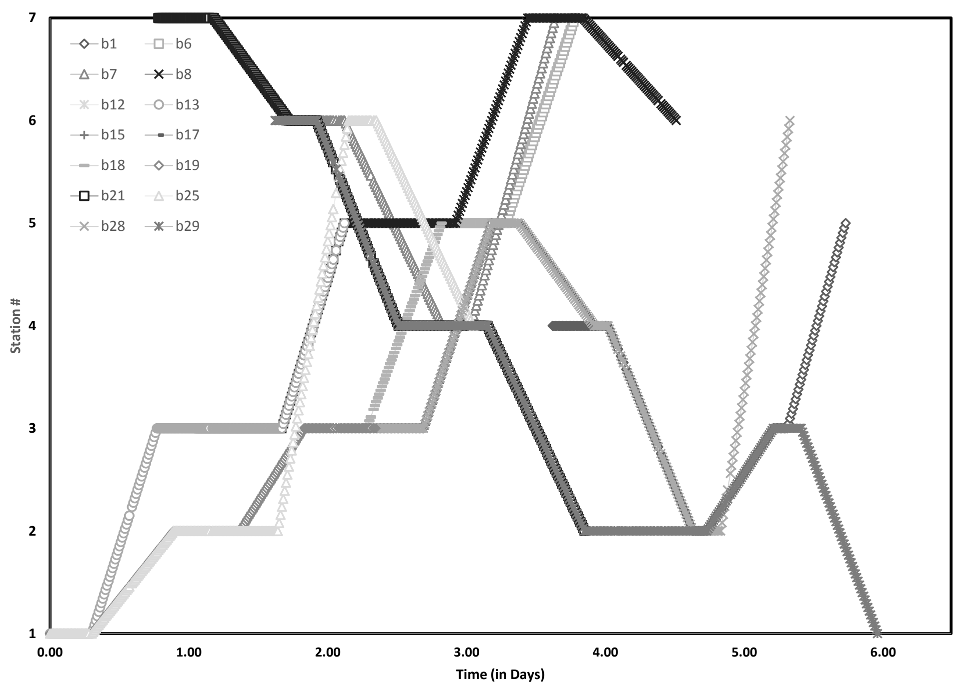


Figure 2.9: Block over time.

schedule and capacity.

2.5.3 Performance of the MIP heuristics

Numerical results of the three set of instances, S, $L1$, $L2$, together with the ones solved by Cplex are reported in Table 2.11, 2.12, and 2.13, respectively. The results for M set are omitted for sake of brevity as we able to draw conclusion similar to the one in S set. The first two columns give information regarding the characteristics of each instance; in term of the number of requests and number of integer variables. The next three columns are the Cplex solutions, including the best solution, the computation time (in seconds), and the optimal gap. The next three columns are the BH solutions. The last three columns are the SH solutions. The OptGap in the MIP heuristics is measured relative to the lower bound of Cplex after time limit has been exhausted or Cplex proves the optimality, whichever occurred first. The last two rows in Table 2.12 and 2.13 give the average and average

Table 2.9: Solution of FTB for $k_1 - k_{21}$.

Req.#	*Itinerary*	*Req.#*	*Itinerary*
k_1	$i_5 \xrightarrow[b_8]{l_{17}} i_7$	k_{12}	$i_2 \xrightarrow[b_{19}]{l_{23}} i_3$
k_2	$i_1 \xrightarrow[b_{19}]{l_4} i_2$	k_{13}	$i_6 \xrightarrow[b_{12}]{l_{11}} i_4 \xrightarrow[b_{12}]{l_{12}} i_2^* \xrightarrow[b_1]{l_{13}} i_3$
k_3	$i_7 \xrightarrow[b_{12}]{l_{10}} i_6 \xrightarrow[b_{12}]{l_{11}} i_4 \xrightarrow[b_{12}]{l_{12}} i_2^* \xrightarrow[b_1]{l_{13}} i_3 \xrightarrow[b_{15}]{l_{14}} i_1$	k_{14}	$i_3 \xrightarrow[b_{18}]{l_{24}} i_5 \xrightarrow[b_6]{l_{25}} i_7$
k_4	$i_7 \xrightarrow[b_{12}]{l_{10}} i_6 \xrightarrow[b_{12}]{l_{11}} i_4$	k_{15}	$i_1 \xrightarrow[b_{19}]{l_4} i_2$
k_5	$i_4 \xrightarrow[b_{18}]{l_{21}} i_2$	k_{16}	$i_4 \xrightarrow[b_{12}]{l_{12}} i_2^* \xrightarrow[b_{b1}]{l_{13}} i_3^* \xrightarrow[b_1]{l_{26}} i_5$
k_6	$i_6 \xrightarrow[b_{12}]{l_{11}} i_4 \xrightarrow[b_{12}]{l_{12}} i_2^* \xrightarrow[b_1]{l_{13}} i_3^* \xrightarrow[b_1]{l_{26}} i_5$	k_{17}	$i_2 \xrightarrow[b_{25}]{l_5} i_6$
k_7	$i_5 \xrightarrow[b_6]{l_{25}} i_7$	k_{18}	$i_2 \xrightarrow[b_1]{l_{13}} i_3 \xrightarrow[b_{15}]{l_{14}} i_1$
k_8	$i_5 \xrightarrow[b_8]{l_{17}} i_7^* \xrightarrow[b_8]{l_9} i_6$	k_{19}	$i_7 \xrightarrow[b_{12}]{l_{10}} i_6 \xrightarrow[b_{12}]{l_{11}} i_4$
k_9	$i_2 \xrightarrow[b_{19}]{l_{23}} i_3 \xrightarrow[b_{18}]{l_{24}} i_5 \xrightarrow[b_6]{l_{25}} i_7$	k_{20}	$i_4 \xrightarrow[b_{28}]{l_{21}} i_2$
k_{10}	$i_7 \xrightarrow[b_{12}]{l_{10}} i_6$	k_{21}	$i_1 \xrightarrow[b_{13}]{l_{15}} i_3 \xrightarrow[b_{13}]{l_{16}} i_5$
k_{11}	$i_3 \xrightarrow[b_{13}]{l_{16}} i_5 \xrightarrow[b_8]{l_{17}} i_7$		

Table 2.10: Solution of FTB for $k_{22} - k_{42}$.

Req.#	*Itinerary*	*Req.#*	*Itinerary*
k_{22}	$i_5 \xrightarrow[b_{17}]{l_{20}} i_4$	k_{33}	$i_4 \xrightarrow[b_{28}]{l_{21}} i_2 \xrightarrow[b_{28}]{l_{22}} i_6$
k_{23}	$i_4 \xrightarrow[b_{28}]{l_{21}} i_2$	k_{34}	$i_7 \xrightarrow[b_{12}]{l_{10}} i_6$
k_{24}	$i_1 \xrightarrow[b_{13}]{l_{15}} i_3 \xrightarrow[b_{13}]{l_{16}} i_5$	k_{35}	$i_7 \xrightarrow[b_{21}]{l_{10}} i_6$
k_{25}	$i_3 \xrightarrow[b_{19}]{l_{19}} i_5 \xrightarrow[b_{17}]{l_{20}} i_4^* \xrightarrow[b_{28}]{l_{21}} i_2$	k_{36}	$i_2 \xrightarrow[b_{19}]{l_{23}} i_3 \xrightarrow[b_{18}]{l_{24}} i_5$
k_{26}	$i_4 \xrightarrow[b_{12}]{l_{12}} i_2^* \xrightarrow[b_{29}]{l_{13}} i_3 \xrightarrow[b_{15}]{l_{14}} i_1$	k_{37}	$i_3 \xrightarrow[b_{15}]{l_{14}} i_1$
k_{27}	$i_2 \xrightarrow[b_{25}]{l_5} i_6$	k_{38}	$i_3 \xrightarrow[b_{13}]{l_{16}} i_5$
k_{28}	$i_2 \xrightarrow[b_{19}]{l_{23}} i_3 \xrightarrow[b_{18}]{l_{24}} i_5$	k_{39}	$i_5 \xrightarrow[b_{17}]{l_{20}} i_4^* \xrightarrow[b_{28}]{l_{21}} i_2$
k_{29}	$i_2 \xrightarrow[b_{25}]{l_5} i_6 \xrightarrow[b_{25}]{l_6} i_4$	k_{40}	$i_1 \xrightarrow[b_{19}]{l_4} i_2 \xrightarrow[b_{25}]{l_5} i_6 \xrightarrow[b_{25}]{l_6} i_4$
k_{30}	$i_4 \xrightarrow[b_7]{l_8} i_7 \xrightarrow[b_8]{l_9} i_6$	k_{41}	$i_1 \xrightarrow[b_{19}]{l_4} i_2 \xrightarrow[b_{25}]{l_5} i_6$
k_{31}	$i_7 \xrightarrow[b_{12}]{l_{10}} i_6 \xrightarrow[b_{21}]{l_{11}} i_4 \xrightarrow[b_{21}]{l_{12}} i_2^* \xrightarrow[b_{29}]{l_{13}} i_3$	k_{42}	$i_2 \xrightarrow[b_{19}]{l_{23}} i_3 \xrightarrow[b_{18}]{l_{24}} i_5$
k_{32}	$i_7 \xrightarrow[b_{21}]{l_{10}} i_6$		

percent deviation relative to Cplex solution for computation time and objective (negative values indicate performance improvement).

Table 2.11: Performance results on instance set Small

Instance ID	NV	CPLEX			BH			SH		
Name-K	-	Objective	Time[a]	OptGap[b]	Objective	Time[a]	OptGap[b]	Objective	Time[a]	OptGap[b]
A1-K42	17394	436750	32.59	0.00	436836	17.72	0.02	436836	17.72	0.02
A2-K100	31830	1533000	55.57	0.00	1533950	30.94	0.06	1538060	26.47	0.33
B1-K120	32701	5625510	133.76	0.00	5797190	41.06	3.05	5627430	42.53	0.03
B2-K220	67249	1407330	>1800	0.05	1526680	178.31	8.48	1531460	206.45	8.82
C1-K42	16162	773349	40.05	0.00	773652	18.34	0.04	773349	21.83	0.00
C2-K100	33318	1728890	>1800	8.73	1805290	110.05	13.15	1778830	152.22	11.62
D1-K41	13095	78663	16.86	0.00	79146	8.93	0.61	78795	8.99	0.17
D2-K100	34759	387728	139.72	0.00	388165	33.91	0.11	388167	31.90	0.11
E1-K42	16216	277825	45.08	0.00	277948	32.04	0.04	282827	21.89	1.80
E2-K100	45298	1498190	>1800	0.00	1499860	36.96	0.11	1504470	42.32	0.42
F1-K42	13512	208144	30.12	0.00	208266	15.077	0.06	208144	30.12	0.00
F2-K100	30848	953166	87.77	0.00	958226	32.55	0.53	958875	26.42	0.60

[a] in seconds, [b] (Objective- Cplex lower bound(after half-hour)/Cplex lower bound(after half-hour))x100.

The proposed MIP heuristics are proven to be efficient to find an optimal or near optimal solution within a short time for instances in set S and M. Compared with Cplex, in 9 out of 12 instances the BH finds solution near optimal solution with maximal optimal gap reported is 0.61%, whereas the SH obtains the optimal solution in 2 out of 12 instances. One may also note that Cplex stops at the maximum time for three instances in group B, C, and E, whereas the proposed heuristics can obtain near optimal solution with much shorter computational effort.

The results displayed in Table 2.12 indicate that the proposed heuristics can obtain good performance on large instances. Where Cplex fails to prove optimality, the proposed heuristics find good solutions which are better than the best solution yield by Cplex, in 45.01% and 42.94% less time than the time allocated for the BH and SH, respectively. In addition, the average percentage deviations are -72.32% and -62.42% for BH and SH in $L1$ instances. With the size of instance increases, the performance of Cplex drops quickly and the proposed heuristics have a high chance to outperform Cplex.

Table 2.13 summarizes the performance on large instance with dense train leg services. As expected the optimality Gap for Cplex is considerably increased when the number of integer variables exceeds 250000. Under the same time limit, the proposed heuristics always find a better solution than Cplex with an average percent deviation of -72.32% and -62.42%

Table 2.12: Performance results on instance set Large 1 ($L1$)

Instance ID	NV	Cplex			BH			SH		
-	-	Objective	Time[a]	OptGap[b]	Objective	Time[a]	OptGap[b]	Objective	Time[a]	OptGap[b]
A3-K200	186939	1601750	>1800	26.79	1567880	802.37	24.68	1497250	1168.92	20.27
A4-K250	232531	4599950	>1800	47.32	3198190	1017.39	16.85	3535370	1173.95	24.18
B3-K200	170435	742516	>1800	25.62	570027	1208.83	2.39	623781	>1800	9.63
B4-K250	222380	1308150	>1800	18.06	1159580	850.16	6.70	1219650	612.01	11.29
C3-K200	174173	3567630	>1800	11.74	3343080	903.18	5.45	3449280	>1800	8.42
C4-K250	218506	6295510	>1800	33.32	6016410	976.00	28.89	5997180	1219.44	28.58
D3-K200	176893	2620720	>1800	36.79	2086300	>1800	16.40	2233670	1015.77	22.02
D4-K250	234301	5982020	>1800	59.34	3159990	1137.04	12.16	3106940	800.53	17.29
E3-K200	175957	3677930	>1800	68.82	1775390	960.138	17.09	1552390	797.02	11.03
E4-K250	218587	4415940	>1800	41.96	2961390	832.998	9.02	2904480	>1800	7.73
F3-K200	197869	2338630	>1800	15.82	2369930	1049.59	17.16	2136980	1045.91	7.20
F4-K250	240379	5259680	>1800	52.29	3946820	1149.63	27.32	3080450	1410.19	10.85
Average			1800	36.49		989.76	15.34		1027.08	15.24
%Deviation						−45.01	−40.44		−42.94	−58.23

[a] in seconds, [b] (Objective- Cplex lower bound(after half-hour)/Cplex lower bound(after half-hour))x100.

for BH and SH, respectively.

If the two MIP heuristics are compared for instances larger than 250000 integer variables, one may notice the results generated by BH dominates SH in most of the instances (9 out of 12 instances in $L2$ set). The reason of better performance of BH over SH could be justified as follows. The former heuristic fixed a subset of the upper level assignment variables w_b (design variables) which accounts only less than 5% of the assignments variables. Once the BH fixes a subset of design variables at an iteration, it also fixes some of the flow variables, i.e., $x_{b,k}$. Therefore, the number of iterations conducted by BH is greater than SH given the time limit. Analogously, the latter heuristics fixed most of the assignment decisions (flow variables) and that supposed to guide the solver to a better solution. However, the changes in the lower level assignments variables from one iteration to another are relatively limited. Hence, the solution space for the BH is less than SH. On the other hand, the BH ability to explore the solution space seems to be extended. BH outperforms SH with regards to the quality of solution and computing times in 9 out of 13 instances in set $L1$ and $L2$.

The tested instances could represent real medium railway systems with 15 terminals, 33 edges, 97 train services, and an average of 250 requests with about 1500 commodities to be shipped. It is also possible to be applied for sub-network of a large railway system to identify detailed territory solution or aggregated national solution with rough knowledge of train schedules. For example, we apply the proposed heuristic to a sub-network of the

Table 2.13: Performance results on instance set Large 2 ($L2$)

Instance ID	NV	Cplex			BH			SH		
-	-	Objective	Time[a]	OptGap[b]	Objective	Time[a]	OptGap[b]	Objective	Time[a]	OptGap[b]
A5-K200	267955	1974740	>3600	44.80	1498470	1067.68	20.68	1608740	1820.68	26.27
A6-K250	360654	6330700	>3600	71.33	2598400	1712.43	12.37	3044110	1824.14	19.41
B5-K200	222236	3543650	>3600	80.73	1051060	1032.53	10.39	1020600	1840.22	9.53
B6-K250	295243	3362640	>3600	64.33	2188590	1977.69	29.42	2695470	1823.29	44.49
C5-K200	256254	4733840	>3600	64.74	2698770	1439.68	21.75	2780570	1811.81	23.48
C6-K250	328333	9360120	>3600	70.29	3675530	1604.87	9.56	4250680	1812.01	15.70
D5-K200	290711	3405130	>3600	63.90	1563830	1260.20	9.83	1785680	1818.02	16.34
D6-K250	352780	4026250	>3600	60.89	2237110	1237.46	16.45	2391250	2191.31	20.28
E5-K200	280433	1849920	>3600	22.08	1759060	1038.18	17.17	1706900	1817.22	14.35
E6-K250	348167	3420810	>3600	55.46	2170880	2067.84	18.92	2980010	>3600	42.57
F5-K200	292189	5355390	>3600	77.70	2348990	2402.36	21.56	2545850	1412.03	25.24
F6-K250	348104	8245660	>3600	71.78	3887800	2063.64	18.93	3629810	>3600	15.80
Average			3600	62.34		1575.38	17.25		1817.07	23.42
%Deviation						−56.24	−72.32		−49.53	−62.42

[a] in seconds, [b] (Objective- Cplex lower bound(after half-hour)/Cplex lower bound(after half-hour))x100.

Canadian Pacific (CP) Railway consists of 23 terminals, 63 edges, 147 train services, and an average of 288 requests with about 3000 commodities to be shipped (details in Appendix B). The proposed MIP heuristics are suitable for an off-line planning for which half-hour is reasonable.

2.6 Conclusion

This chapter explores the routing and scheduling of rail shipments of hazardous materials with blocking decisions. A transportation system where different customers make their requests for railcar moves, i.e., both hazmat and non-hazmat freight, between different origins and destinations, with specific requirements on delivery times was considered. The mathematical model minimizes total cost, i.e., the earliness, tardiness, classification and holding costs acquired to fulfill all the demands, while imposing risk thresholds constraints associated with hazmat transportation. The problem is to determine for each demand (a) the itinerary that must follow from its origin yard to destination yard (if not outsourced), (b) the sequence of trains that it must assign along the route so that the request time, and train capacities constraints are satisfied, and (c) the blocks used to transport it for each train leg along its route. A non-linear mixed-integer programming and two MIP heuristic-based solutions are proposed for generating the trip plans. Through computational experiments, it may be concluded that the MIP heuristics provide good solutions for medium size instances while solving the mixed integer programming formulation can be computationally expensive. Comparing the two proposed MIP heuristics, the BH outperforms the SH solutions for large instances with a large number of train services, on average percent deviations of 26.35% and average of 13.29% less computational time.

Chapter 3

Modeling and solution method for HTPs with train scheduling decisions

An Integrated Train Scheduling and Hazardous Materials Trip Planning Problem

Omar A. Abuobidalla, Mingyuan Chen, Satyaveer S. Chauhan

This manuscript is under review in International Journal of Rail Transportation (September 2019)

This chapter investigates the routing and scheduling of rail freight of hazardous materials problem with train scheduling decisions considering risk distribution function. We consider the problem of minimizing the weighted sum of the cost of serving the commodities plus risk distribution function using well-defined measures, either the maximum population exposure, the difference between the maximum and minimum transport risk, or the mean absolute deviation of the transport risk while limiting the population exposure below the given risk threshold. Non-linear mixed integer programming models and heuristic method are proposed for preparing the shipment plans and determining the schedule of train services. Numerical examples are provided to study and analyze different risk distribution considerations.

3.1 Introduction

The safety of hazardous materials (hazmat) transportation has become an important national and international issue (Ingolfsson and Erkut, 2000). Hazardous materials are routinely shipped through and temporarily stored near the population centers in vast volumes. Although railway companies have favorable safety records in moving hazmat shipments (Oggero et al., 2006), the possibility of spectacular events resulting from multicars incidents, however low, does exist, and the consequence can be significant. These incidents may happen while a train is stationary or moving including loading and unloading process at station. The risk of low-probability of high-consequence (LPHC) accidents resulting from transporting Toxic Inhalation Hazmat (TIH) materials can be potentially catastrophic in multiple fatalities (Sherali et al., 1997). The rail disaster in Lac-Mégantic, Quebec, resulted in 47 fatalities in 2013, is an example of LPHC event. Generally speaking, shippers prefer to ship in bulk and long-distance hazmat transportation by railway services as the volume of one railcar carries almost four trucks. According to the most conducted statistics in 2012, railway companies shipped almost 111 million tons of hazmats in the United States (DOT, 2017c) and 26 million tons of hazmats in Canada (DOT, 2017b). Among the different modes used to ship hazmats, the railway transportation of hazmats becomes an increasingly pressing issue due to safety and security concerns related to rail transportation of hazmat.

It is evident from accident records that hazmat train accidents or derailments would impact populations that are not receiving a proportional share of the benefits from hazmat transportations or fair compensation for the risk exposures (Romero et al., 2016). The population living along a major rail track connection is likely exposed to the risks regardless of whether or not they benefit from hazmat transportation. This raises the question of how to spread the risks over the considered population. Risk equity or equilibration can be defined as the fair distributing of risk through population (Fontaine et al., 2016). An example of equity-based public opposition is the shipment spent nuclear fuel rods from nuclear power plants to the proposed repository at Yucca Mountain in Nevada (USA) (Erkut et al., 2007). It is well recognized that equity can be improved by spreading a shipment into multiple routes (Gopalan et al., 1990). However, rail rerouting is different from highway rerouting of hazards in that railroad network does not offer many routing options as highway network (McClure et al., 1988). In order to spread risk in railway transportation, the rail carriers have to consider risk spreading function in solving train scheduling (Fang et al., 2017) and/or train makeup (Hosseini and Verma, 2018) problems.

Different than hazmat transport by road, hazmat transport by rail is subject to well-defined schedule, including its path, en-route stops, and related timetable (Bersani et al., 2016). One approach to enhance the safety in transporting hazmats is to determine optimized train schedules with some information of the demand characteristics, population density, and atmospheric condition, while an alternative routing does not always exist (Glickman et al., 2007). The train scheduling problem is hard problem on its own even when the risk associated with hazardous material shipments are not taken into consideration (Zhu et al., 2014), due to its complexity regarding interacting planning processes. Although trip plan generation process and train scheduling problem are crucial to freight train operations (Cordeau et al., 1998; Huntley et al., 1995), hazmat related engagements are rather few (Fang et al., 2017).

In this chapter, we integrate the train scheduling decisions into trip plan generation process of hazmat. The main problem is that of finding minimum risk trip plans and determining trains schedules while limiting the transport risk to given thresholds and distributing the risk associated with hazmats transportation. We use different quantities to measure the consequence in distributing the risk, either the maximum population exposure, the difference between the maximum and minimum risk, or the mean absolute deviation of the population exposure. A heuristic method is proposed to solve the rail freight routing and scheduling problem. The heuristic generates itineraries associated with much higher levels of equity in distributing risk than those dispatching strategies without considering risk spreading function. Numerical examples are provided to study and analyze different risk spreading functions.

3.2 Related literature

As the proposed investigation related to multiple sub-areas within hazmat transportation domain, we organize the literature review into three groups: routing and scheduling of hazmat problem; equity in distributing risk; and train scheduling and trip plan problem.

Routing and scheduling: Rerouting of hazmat is one of the main issues in hazmat transportation (Erkut and Ingolfsson, 2000; Glickman et al., 2007; Kara and Verter, 2004). It deals with the selection of a set of alternative itineraries from the comprehensive list of itineraries for all origin-destination pairs on a given network to minimize the total risk. Different aspects of rerouting of hazmat problem were studied in hazmat logistics literature. Verma et al. (2011) integrate the frequency of trains decisions into the trip plan generation process. Romero et al. (2016) studied location-routing problem while considering equity in distributing risk. Integration of routing and scheduling decisions becomes crucial as the population exposure and probability of an accident vary over time (Cox and Turnquist, 1986; Miller-Hooks and Mahmassani, 2000; Nozick et al., 1997a; Szeto et al., 2017). In addition to the selection of the set of itineraries for the customer requests, one must determine the best times to dispatch the vehicles and determine the waiting times along routes. Nozick et al. (1997a) observed that the en-route stops of vehicles can be used as dispatching strategy to take advantage of the time-varying nature of the accident probabilities and population exposure in reducing the risk associated with hazmat transportation. Erkut and Alp (2007b) concluded that the en-routes stops allow the carrier to generate routes with much lower level of risk than those policies where no waiting is allowed. Inequity in distributing risk is often stemmed from the operator's routing and scheduling decisions (Bianco et al., 2009). The aim of equity in risk is to maximize the distributing of risk while limiting risk in any population zone to given risk threshold.

Equity in distributing risk: Equity spatial distribution of risk has considerably received attention from hazmat researchers over the past decade (Bell, 2006; Gopalan et al., 1990;

Zografos and Androutsopoulos, 2008; Zografos and Davis, 1989) as the community opposition to the routing of vehicles carrying hazmat close to population center in vast volumes, and the overloading of certain segments with hazmat flows may increase in the incident probability. Zografos and Davis (1989) proposed a multi-objective model that takes into account equity considerations by limiting risk on links to certain thresholds. The objective of the model is to minimize the total risk, the risk level imposed on certain population groups, the travel time and property damage. The authors concluded that imposing equity into routing and scheduling decisions increases the total risk by 35%. Bell (2006) and Bell (2007) separately proposed a min-max model to minimize the maximum risk on the links in which the transportation network is embedded. The traditional method to consider risk equity is that based on the generation of different paths that share few links (Akgün et al., 2000). Carotenuto et al. (2007) designed two heuristics based on Yen's algorithm considering the risk resulting from selecting similar paths and equity in spreading risk. Two phases procedure was designed to tackle the considered problem. In the first phase, the set of possible paths for each request is determined and then the commodities are routed and scheduled by assigning one of the available routes and a starting time to each vehicle to avoid any pair of vehicles that scheduled too close. Zografos and Androutsopoulos (2008) proposed a heuristic method to obtain the set of alternative non-dominated hazardous material paths with considerations of cost and risk minimization. The planning of the emergency response team decisions was explicitly considered into minimum path selection process. Kang et al. (2014) extend the Value-at-Risk (VaR) into multi-trip multi hazmat context. The model determines the minimum global VaR while constraining risk on the links to given thresholds. Recent methods motivated by game theory have been proposed to ensure a more equitable hazmat transport network (Bianco et al., 2012). One may notice that most of the risk equity works have been done in road transportation and few engagements in railroad transportation (Bersani et al., 2016; Chin et al., 2009; Fang et al., 2017).

Transportation of hazmat materials in railway context differentiates from road transportation in the number of factors. A train typically carries multiple types of materials, i.e., hazmat and non-hazmat. Another important characteristic of railway context, from an equity assessment perspective, is that it involves multiple hazmat shipments with different service requirements, in which must be consolidated, routed and scheduled by a set of train services. In this case, the operator may not only aims to limit the risks to certain thresholds but also must also consider risk spreading over all the links of the railway network. One approach to spread the transport risks is to generate different routing alternatives with a slight variation of one another (Hosseini and Verma, 2017,1; Kuby et al., 1997). Unlike road transportation, railway vehicles bound for various yard consolidate together and move at the same speed along their itinerary.

Train scheduling and trip plan: Hazmat routing and train scheduling problem often divided into two nested subproblems: trip plan and train scheduling problem. One approach to tackle the routing and train scheduling of hazmat problem deals with train scheduling problem given the trip plans of the considered requests. That is, a routing problem is first solved and then train scheduling decisions determined given the trip plans of the requests. In non-hazmat transportation, Cacchiani et al. (2008) modeled and designed a heuristic method to solve a non-periodic train timetabling problem. The model aims to maximize the profit of the schedule trains subject to track capacity constraints and prevent too close departure/arrival of trains at terminals. Caprara et al. (2002) studied the periodic version of train timetabling problem. If hazmats involve in planning, the routing and scheduling decisions become important to maximize the equity in distributing risk in addition to minimize total transport risk. Bersani et al. (2016) proposed a binary linear programming model to reschedule a set of hazmat trains to minimize the average and maximum population exposure. The authors demonstrated that variations of the timetable decrease the average and maximum exposure through a case study in Liguria and Piedmont regions in Italy. Another comprehensive method is to combine the routing and train scheduling decisions by a single optimization model. Fang et al. (2017) integrate routing and scheduling of hazmat freight with due dates while considering equity by constraining risk on links to the given thresholds. A mixed-integer programming model and a heuristic procedure are proposed to determine the timetable of the trains including their speeds and trip plans of the customer requests. The authors observed that the performance of the heuristic closely depends on the given risk thresholds. A considerable improvement in safety can be achieved by integrating routing and train scheduling decisions and also more equitable hazmat transport network (Bianco et al., 2009).

It is clear from the hazmat literature that the problem of distributing the risk equitably over the population zones in the railway industry is still need further attention (Erkut et al., 2007). In this chapter, in addition to our main objective of finding a set of trip plans of the considered requests while limiting risk on train services to certain risk thresholds, we also attempt to maximize the risk spreading using well-defined quantities, either by minimizing the maximum population risk or the difference between the maximum and minimum population risk or the mean absolute deviation of the risk sustained by the population living along links. A request typically involves multiple train services scheduled together to fulfill various customer requirements. As the risk evaluation pertains to each alternative itinerary, i.e., population exposure and/or atmospheric class may differ over time, the trip planning and train scheduling decisions are intertwined. Therefore, we propose a mixed integer mathematical formulation for the consider train scheduling and trip plan problem. The linear version of the Gaussian Plume Model (GPM) in Abuobidalla et al. (2019c) was borrowed to measure the risk from hazmat transportation, and a heuristic was designed to solve the train scheduling and trip plan problems. Hereafter, we refer to this problem as *hazardous material trip plan problem with train scheduling decisions* (HTPTD).

The chapter is organized as follows. The considered problem is defined and the different versions of risk spreading considerations are presented in section 3.3. The proposed solution is described in section 3.4. We present our experimentation results in section 3.5. Conclusions of this work are given in section 3.6.

3.3 Problem statement

We consider a railway company that operates $|S|$ train services within a railway network $G(V, S)$, where V and S are the set of terminals and train services, respectively. The set S is predefined in advance including its route and capacity at the tactical level, given the information on the expected demand between each pair of terminals in the network. Its schedule, however, is a decision to be made. Each direct train service $s \in S$, a train moves nonstop between two yards, starts at yard o_s, terminates at yard d_s and must be defined by a set of operational characteristics, i.e., the operation start time τ_s^o, cutoff time τ_s^c, schedule departure τ_s^d at origin yard, schedule arrival τ_s^a at destination yard, and maximum number of cars U_s can be hauled by a train service. The cutoff time specifies the minimum time in which the operator guarantees that the inbound freight will be classified to be pulled along with the planned train service. A railway operator, a central decision maker, is in charge to manage various customer requests, denoted by $k \in K$, for a carload moves within a railway network. In response to these planned train services, the operator receives a sequence future requests for carload moves, hereafter called request. For each request k in K, the operator is given the pickup yard o_k, delivery yard d_k, and earliest available time τ_k^{AL} at the origin yard. The operator can either accept or serve the demand by a partner, if the capacity of train services are fully utilized and/or risks associated with hazard shipment exceed the given thresholds. In the case demand $k \in K$ is accepted, the operator will assign the demand to a sequence of train services including the blocking path along the route. At the beginning of the request's itinerary, a shipment will be pulled on the receiving tracks to be classified at o_k. After a demand is sorted, it will be delivered to its yard by a sequence of train services. In case a demand $k \in K$ cannot be delivered by its train service, the operator may use the service of a partner (outsource the request) and be charged with a cost of ϕ_k, sufficient large number. We assume the service of the partner is always available for shipment albeit at a higher cost, i.e., marine, or road service. We use different risk reduction strategies aiming at reducing the transport risk, i.e., rerouting of hazmat commodities and transferring the hazmat to the transport network of a partner. Each of these risk reduction strategy has its safety benefit and corresponding cost for implementation. In most cases, transferring the hazmat risks to the transport network of the third party could be useful in reducing the total risk (see Azad et al., 2016; Jabbarzadeh et al., 2019) and might be also help in maximizing the risk spreading.

Over the progression of serving the demands, the operator incurs certain operating costs including shipping cost, re-sorting cost, and commodity holding cost during the journey. The latter cost arises when the railcars idle without being in (re)sorting or transfer process. In addition to the costs for serving the requests, the operator evaluates the risk associated with hazmat transportation.

In compliance with the railway policy and government regulation, the operator assesses the risk associated with hazmat transportation when generating trip plans. The operator also attempts to distribute the risks associated with hazardous materials shipments. The objective is to limit the public risk at given risk thresholds, and maximizing the equity in distributing the transport risk along with the planned services either by minimizing the maximum population risk, the difference between the maximum and minimum risk, or the mean absolute deviation of risk, based on the interest of the decision maker. In measuring the risk, we adopt a worse-case approach using consequence as the measure of transport risk.

Solving the rail operation planning and scheduling problem is to determine the train scheduling and car distributing decisions to provide the required services to customers and to minimize the total cost including the cost of shipping and sorting commodities. We also consider the equity in distributing the risk associated with transporting hazmats by imposing risk thresholds constraints and minimizing the maximum population exposure for the planned services for one of the proposed model. Risk spreading might be interpreted as a further objective to be attained, without overloading any train service or part of the network. The solution of the problem is to determine for each demand (a) the itinerary that must follow from its origin to its destination yard (if not outsource) including the blocking path, (b) the sequence of trains that it must assign along the route so that the trains capacities constraints, and risk thresholds are satisfied, and also determines the timetable of planned services (illustrated in Figure 3.1).

3.3.1 Risk assessment model

In this research, we focus on hazardous materials that are airborne at an accidental release into the environment, i.e., chlorine and ammonia, as TIH/PIH materials present

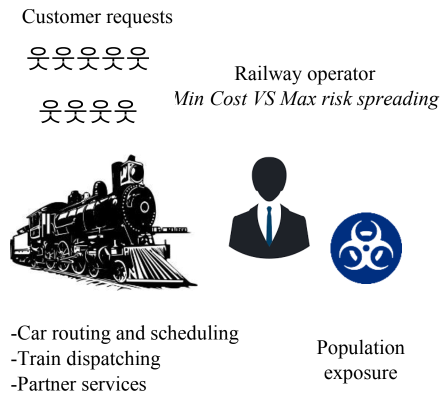


Figure 3.1: Schematic diagram of the HTPs with train scheduling decisions.

the greatest risks. Chlorine is mainly used for purifying potable and wastewater and also used in as chemical intermediary in different industries, for goods ranging from PV pipes to shampoo. Ammonia is a commercial fertilizer and mainly used in the agricultural farms. Such hazardous materials belong to TIH/PIH materials. Because most carriers tend to exhibit risk-averse when transporting TIH/PIH materials and the lack of information to estimate precisely the probability of low probability of high consequence, we focus on the consequence in evaluating the risk. In particular, we use the most popular air dispersion models in Arya et al. (1999); Zhang et al. (2000), namely the Gaussian Plume Model (GPM), to assess the public risk. The effects of an accident involving airborne hazmats might be quantified in term of the exposed population, the total number of people exposed to the possibility of an undesirable consequence due to the hazardous materials releases (Batta and Chiu, 1988). For instance, the immediately dangerous life and health (IDLH) for propane exposure are 4,200,000 ppm for fatality and 600,000 ppm for injuries. At certain IDLH level, we need to identify a safety distance threshold. The number of people residing at the intersection of the polygons is corresponding to the population zones. The overlaid of the safety distance thresholds is the population exposure. Both the terminals and routes consider the sources of hazmats releases. Following Kara et al. (2003), we assumed a rectangular and circle dangerous zone for both edge and terminal source, respectively.

A summary of the quantitative risk assessment is given in Table 3.1 and illustrated in Figure 3.2. We refer to Verma and Verter (2007) and Abuobidalla et al. (2019c) for the technical details of the GPM and piecewise linearization for the transport risk, respectively.

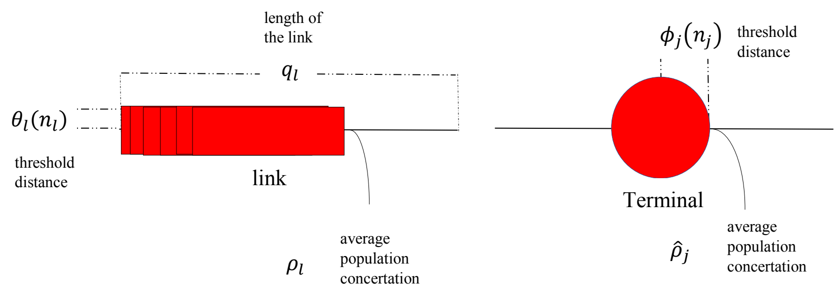


Figure 3.2: Danger rectangular and circle.

Table 3.1: A summary of GPM for terminal and route.

Public Risk[a]	***Parameter***[b]	***Approximation function***
$PR_j^{node} = \pi\Phi_j(n_j)\hat{\rho}_j$	*Threshold area*	$\Phi_j(n_j) = \left[\sqrt[b_j+d_j]{\frac{n_j Q}{\pi\ u_j\ a_j\ c_j\ \bar{\mathcal{C}}}}\right]^2 : j \in d_s$
$PR_s^{edge} = 2\Theta_s(n_s)\rho_s q_s$	*Threshold distance*	$\Theta_s(n_s) = \left[\sqrt[b_s+d_s]{\frac{n_s Q}{\pi\ u_s\ a_s\ c_s\ \bar{\mathcal{C}}}}\right] : s \in S$

[a] $PR_j^{node}(PR_s^{edge})$: Population exposure at terminal i (along service s).
[b] Parameters is function of chemical characteristics and volume of hazmat.

3.3.2 Problem assumptions

In developing the mathematical model, we make the following assumptions:

- The route of each train $t \in T$ consists of a set of consecutive direct train legs defined by S_t, is given by the service provider and is not a decision variable. That is, for each train service we are aware of its origin f_t, destination l_t, service legs, en-route stops, and capacity.

- Each demand will be shipped following one of the available itinerary (i.e., Li et al., 2017). It leads to that the demand will not split during transportation. Such an approach is a common practice in North America railway companies, operating on double consolidation process, loaded and empty car grouped to construct blocks, and blocks grouped to makeup trains. In some cases, transporting dangerous goods should be routed using a single path to reduce the transport risk (Erkut and Gzara, 2008).

- All demands, in terms of the number of cars to be shipped per week, are known in advance and static based on historical data or negotiated contracts with customers. For the given and known demands, the railway operator has sufficient capacities for yard and train operations to satisfy the demand.

- The proposed model aims to find a comprehensive rail freight distributing and train scheduling decisions from single rail carrier perspective while explicitly take into considerations the equitable distribution of risk. In the case of multiple carriers manage by a regulator, one may extend one of the available models in hazmat network design literature (Erkut and Gzara, 2008; Kara and Verter, 2004) or in toll settings of hazmat transportation literature (Bianco et al., 2012; Marcotte et al., 2009).

- The hazmat transported on train possess similar chemical characteristics. Consistent with the prevailing literature on hazmat logistic, the undesirable consequences of their interactions can be neglected.

3.3.3 Mathematical model

We developed three versions of HTPs with train scheduling problem, with various considerations of risk spreading function. The first two models focus on the maximum population exposure among the train services while the last one minimizes the mean absolute deviation of risk subject to risk thresholds constraints. To improve the readability of this chapter, sets, parameters, and variables of the proposed models are given in Table 3.2-3.3.

Table 3.2: Set, indices, parameters, and variables (Part 1 of 2).

Sets and indices	
T	Set of train services, index by $t \in T$.
K	Set of requests, index by k *or* $k' \in K$.
I	Set of terminals in G, index by i or $j \in I$.
S	Set of direct services provided by the carrier, index by s or $s' \in S$.
S_t	Order set of direct services covered by train t, $S_t = \{l_t, ..., f_t\} \subseteq S$.
S_k	Subset of services that a request k can pulled along, index by $s \in S$.
S_i^+	Emanating services from node i, index by $s \in S$.
S_i^-	Ending services at node i, index by $s \in S$.
Parameters	
f_t	First departure terminal of train t, $f_t \in I$.
l_t	Last arrival terminal of train t, $l_t \in I$.
v	Average train speed.
q_s	Integer corresponds to train number for direct train service s belong to, $q_s \in T$.
o_k	Origin yard of request k, $o_k \in I$.
d_k	Destination yard of request k, $d_k \in I$.
o_s	Origin yard of direct train service s, $o_s \in I$.
d_s	Destination yard of direct train service s, $d_s \in I$.
$\lambda_{s,s'}$	Indicator = 1 if service s' is immediately scheduled after service s; 0 otherwise, $\lambda_{s,s'} = \{1 \ \forall \ s, s' \in S : o_{s'} = d_s \ \& \ q_s = q_{s'}\}$.
$\theta_{s,s'}$	Indicator = 1 if service s and s' travel on the same train leg; 0 otherwise, $\theta_{s,s'} = \{1 \ \forall \ s, s' \in S : o_{s'} = o_s \ \& \ d_s = d_{s'}\}$.
ρ_s	Average population concentration along the direct train service s, $s \in S$.
q_s	Distance of the direct train service s, $s \in S$.
$\widehat{\rho_j}$	Average population concentration at yard j, $j \in I$.
U_s	Maximum number of railcars can be hauled by a train service s, $s \in S$.
$n_s(n_j)$	Number of dangerous goods shipped along direct train service s (through terminal j).
ψ	Conversion factor for risk spreading.
c_s^T	Cost to ship a request on service s, $s \in S$.
c_s^H	Cost to hold a request at terminal o_s per unit time, $s \in S$.
ϕ_k	Cost to outsource request k by a partner, $k \in K$.
D_k	Number of regular railcars in request k to be shipped, $k \in K$.
H_k	Number of hazmat railcars in request k to be shipped, $k \in K$.
$\Theta(n_j)$	Threshold area to ship n_j hazmat freights through terminal j, $j \in I$.
$\Phi(n_s)$	Threshold distance to ship n_s hazmat freight along train service s, $s \in S$.
d	Maximum inventory time a commodity can be hold at terminal without any additional charges.
$a(b)$	Minimum (Maximum) time between the departure and arrival of two consecutive direct train services, i.e., $\lambda_{s,s'} = 1$.
c	Minimum safety interval between two services travel on the same leg, i.e., $\theta_{s,s'} = 1$.
Variables	
Integer	
$x_{k,s}$	= 1 if commodity k is shipped by service s; 0 otherwise.
$y_{s,s'}$	= 1 if service s' departures before service s on the train leg; 0 otherwise.
z_k	= 1 if request k served by a partner; 0 otherwise.

Table 3.3: Set, indices, parameters, and variables (Part 2 of 2).

Continuous	
τ_s^o	Schedule operation start time of the direct train service s at yard $o_s \in I$.
τ_s^c	Schedule cutoff time of the direct train service s at yard $o_s \in I$.
τ_s^d	Schedule departure time of the direct train service s at yard $o_s \in I$.
τ_s^a	Schedule arrival time of the direct train service s at yard $d_s \in I$.
p_s	Population exposure due to ship n_s hazmats along service s, $s \in S$.
p^{max}	Maximum population exposure among the planned services, $p^{max} = \max_{\forall s \in S} p_s$.
p^{min}	Minimum population exposure among the planned services, $p^{min} = \min_{\forall s \in S} p_s$.
p_s^{mad}	Absolute deviation of the population exposure from average population exposure for service s.
$a_{k,j}$	Arrival time of request k at yard $j \in I$.
$h_{k,s}$	Amount inventory for request k to be hauled on service $s \in S$.

HTPTD with risk spreading 1

We propose a min-max model, referred to as *HTPTD with risk spreading* 1, in which the model minimizes the total cost from serving the requests and maximum population exposure for the planned services. Hence, we aim at the spatial distribution of risks by balancing the risk through the services of the railway network in addition to limiting the total population exposure along with the planned services to given risk thresholds. The mathematical formulation is given in (P_3).

$$(P_3) \quad Min\ Z_1 = \sum_{k \in K} D_k \Bigg[\overbrace{\sum_{\substack{j \in J: \\ j = d_k}} a_{k,j} + \sum_{s \in S_k} \Big[c_s^T x_{k,s} + c_s^H h_{k,s} \Big]}^{\text{Serving costs}} + \overbrace{\phi_k z_k}^{\text{Partner cost}} \Bigg] + \overbrace{\psi p^{max}}^{\text{Risk spreading}}$$

s.t.

$$\sum_{s \in S_k \cap S_i^+} x_{k,s} - \sum_{s \in S_k \cap S_i^-} x_{k,s} = \begin{cases} 1 - z_k & \forall k, i : i \in o_k \\ z_k - 1 & \forall k, i : i \in d_k \\ 0 & \forall k, i : i \notin o_k \ nor\ d_k \end{cases} \tag{16}$$

$$\sum_{k \in K} D_k x_{k,s} \leq U_s \qquad \forall s : s \in S \tag{17}$$

$$\sum_{s \in S_k : d_s = o_k} x_{k,s} < 1 \qquad \forall k : k \in K \tag{18}$$

$$a_{k,j} - \tau_s^c + M(x_{k,s} - 1) \leq 0 \qquad \forall k, s, j : j = o_s,\ s \in S_k \tag{19}$$

$$\tau_s^a \geq \tau_s^d + q_s / v \qquad \forall s : s \in S \tag{20}$$

$$a_{k,j} - \tau_s^a + M(1 - x_{k,s}) \geq 0 \qquad \forall k, s, j : j = d_s,\ s \in S_k \tag{21}$$

$$h_{k,s} - \tau_s^o + M(1 - x_{k,s}) + a_{k,j} + d \geq 0 \qquad \forall k, s, j : j = o_s, \;\; s \in S_k \tag{22}$$

$$b \geq \tau_{s'}^o - \tau_s^a \geq a \qquad \forall s, s' : \lambda_{s,s'} = 1 \tag{23}$$

$$\tau_s^d - \tau_{s'}^d + M y_{s,s'} \geq c \qquad \forall s, s' : \theta_{s,s'} = 1 \tag{24}$$

$$y_{s,s'} + y_{s',s} = 1 \qquad \forall s, s' : \theta_{s,s'} = 1 \tag{25}$$

$$2\Theta_s\Big(\sum_{k \in K} H_k x_{k,s}\Big)\rho_s q_s + \pi\Phi_j\Big(\sum_{k \in K} H_k x_{k,s}\Big)\hat{\rho}_j \leq R_s \qquad \forall s, j : j = d_s \tag{26}$$

$$2\Theta_s\Big(\sum_{k \in K} H_k x_{k,s}\Big)\rho_s q_s + \pi\Phi_j\Big(\sum_{k \in K} H_k x_{k,s}\Big)\hat{\rho}_j \leq p^{max} \qquad \forall s, j : j = d_s \tag{27}$$

$$h_{k,s} \geq 0 \;\; \forall k, s; \quad y_{s,s'}, x_{k,s} \in \{0, 1\} \qquad \forall k, s, s' \tag{28}$$

$$\tau_s^o, \tau_s^c, \tau_s^d, \tau_s^a \geq 0 \qquad \forall s \tag{29}$$

$$p^{max} \geq 0 \tag{30}$$

The objective function Z_1 in the above-presented model (P_3) is to minimize the cost from serving the railway requests, and the maximum population exposure over the planned services. The first term in Z_1 aims at delivering railway requests at their destination yards as early as possible, while the second term minimizes the costs of transporting and holding the commodities. The cost of using partner services (if any) is given in the third term in Z_1 and the last term minimizes the maximum population exposure. The conversion factor ψ in Z_1 is introduced to perform tradeoff analysis between the total costs and maximum risk. That is, if spreading risk more important to the operator then higher conversion factor might be assigned to ψ, and vice versa if the total cost is more important. Constraints (16) are commodity flow conservation constraints. Constraints (17) are train capacity constraints for the planned services. Constraints (18) are tour elimination constraints. Constraints (19) ensure that requests arrive before the cutoff time of the train services along their itineraries. Constraints (20) determine the arrival times of the train services. Constraints (21) determine the time of arrival for the requests at en-route stops along the routes. Constraints (22) define the holding times for the requests at terminals along the shipment's itinerary, i.e., $h_{k,s} = \tau_s^o - a_{k,j} - d$. Constraints (23) guarantee that minimum and maximum separation time intervals between any pair of consecutive services. Constraints (24)-(25)

ensure one service dispatches along the same service leg for safety reasons, not less than c interval time between the departure of those services. Constraints (26) ensure that the total population exposure is no greater than the given thresholds, the first term in Constraints (26) is the sum of population exposure along the routes and the second term is that at yards. This risk thresholds could be mandated by a regulatory body external to the railway company or could correspond to a decision made internally by management to adhere to specific limits on population exposure. The capacity and risk thresholds constraints may cause infeasibility, however, artificial linked are added to ensure the delivery of all requests. This has been done by introducing z_k variables, some shipments can reach their destination yards via partner services with high costs. Constraints (27) define the maximum population exposure. Constraints (28) are integer variable requirements. Constraints (29)-(30) are non negativity restrictions.

HTPTD with risk spreading 2

We also propose another version of the min-max model aiming at minimizing the total cost from serving the requests and difference between the maximum risk from the minimum population exposure for the planned services, referred to as *HTPTD with risk spreading* 2. Risk spreading can be achieved by limiting the population exposure of the planned services and minimizing the difference between the maximum and minimum population risk. Detail of the model is given below.

$$(P_4) \quad Min\ Z_2 = \sum_{k \in K} D_k \Bigg[\overbrace{\sum_{\substack{j \in J \\ :j=d_k}} a_{k,j} + \sum_{s \in S_k} \Big[c_s^T x_{k,s} + c_s^H h_{k,s} \Big]}^{\text{Serving costs}} + \overbrace{\phi_k z_k}^{\text{Partner costs}} \Bigg] + \overbrace{\psi \Big[p^{max} - p^{min} \Big]}^{\text{Risk spreading}}$$

$s.t.$

$$(16)-(29)$$

$$2\Theta_s \Big(\sum_{k \in K} H_k x_{k,s} \Big) \rho_s q_s + \pi \Phi_j \Big(\sum_{k \in K} H_k x_{k,s} \Big) \hat{\rho}_j \geq p^{min} \quad \forall s, j : j \in d_s \tag{31}$$

$$p^{max}, p^{min} \geq 0 \tag{32}$$

Objective function Z_2 in the above presented model (P_4) is similar to the objective function Z_1 except for the last term. The last term in Z_2 computes the difference between the maximum and minimum population exposure. Constraints (31) compute the minimum population exposure among the train services. Constraints (32) are non-negatively constraints.

HTPTD with risk spreading 3

The third model, referred to as *HTPTD with risk sperading* 3, minimizes the mean absolute deviation of the population exposure in addition to the total cost from serving the requests.

$$(P_5) \quad Min\ Z_3 = \sum_{k \in K} D_k \Bigg[\overbrace{\sum_{\substack{j \in J: \\ j = d_k}} a_{k,j} + \sum_{s \in S_k} \Big[c_s^T x_{k,s} + c_s^H h_{k,s} \Big]}^{\text{Serving costs}} + \overbrace{\phi_k z_k}^{\text{Partner}} \Bigg] + \overbrace{\psi \Bigg[\frac{\sum_{s \in S} p_s^{mad}}{|S|} \Bigg]}^{\text{Risk spreading}}$$

$s.t.$

$$(16)-(26), (28)-(29)$$

$$2\Theta_s \Big(\sum_{k \in K} H_k x_{k,s} \Big) \rho_s q_s + \pi \Phi_j \Big(\sum_{k \in K} H_k x_{k,s} \Big) \hat{\rho}_j \leq p_s \qquad \forall s, j : j = d_s \tag{33}$$

$$\left| p_s - \frac{\sum_{s' \in S} p_{s'}}{|S|} \right| \leq p_s^{mad} \qquad \forall s : s \in S \tag{34}$$

$$p_s \geq 0 \qquad s : s \in S \tag{35}$$

$$p_s^{mad} \geq 0 \qquad s : s \in S \tag{36}$$

Objective function Z_3 in the above presented model (P_5) is similar to the objective function Z_1 except for the last part. The last term in Z_3 minimizes the mean absolute deviation of the population exposure. Constraints (33) compute the population exposure for each train service, while constraints (34) compute the absolute deviation of the risk from the average risk. The inner terms in (34) determines the deviation of the population exposures resulting from transporting hazmat railcars using different service legs. Constraints (34) measure the variation across different train services. Note that smaller values of variability in risk indicate the higher distributing in risk. Clearly higher values of p_s^{mad} indicate large variation in transport risk as a result of operator routing and scheduling decisions, which may raise concern for the communities and government agencies. Model (P_5) ensures that solutions with low average risk and high variability across different train legs are minimized. Note that we are interested in the variability of the risk, above or below the average population exposure, and hence the equation in using the absolute bracket. In other words, the presence of the risk variability term in the objective function provides a high level of spreading of the risk. Constraints (35) are non-negatively constraints.

Problems $P_f, f = 3, 4, 5$ is a version of Multicommodity Minimum Cost Network Flow Problem (MCNFP) with train scheduling decisions, which is known to be NP-hard (Cacchiani et al., 2008; D'Ariano and Pranzo, 2009; Magnanti and Wong, 1984; Minoux, 1989), with nonlinear constraints to consider the public risk and equity in distributing risk. Although the special structures of the MCNFP can be solved in polynomial time, some other variants of the MCNFP are intractable. An integer flow for the minimum cost multicommodity flow is proved to be NP-complete (Even et al., 1976b; Li et al., 2017). Furthermore, the flow over time MCNFP is known to be NP-hard (Cai et al., 2001). The train scheduling problem is a version of the train timetabling problem (TTP), which proven to be NP-hard. Caprara et al. (2002) showed that the TTP is NP-hard as a generalized of the maximum stable set problem. In this chapter, we design a heuristic method to solve the considered problem.

3.4 Solution method

In this section, a heuristic solution method is presented to solve the considered HTPTD with risk spreading function. The non-linear programming model will be first reformulated as an MIP model and solved using a commercial solver. Then, a heuristic search procedure is performed, which involves calling a mixed integer programming solution subroutine to solve MIP sub-models iteratively to improve the incumbent solution by optimizing a single train service at a time. The solution of the MIP sub-model should correspond to improve train schedules and followed by solving the rail freight planning problem. The search will stop when the number of local searches is achieved or the total computational time has reached a given limit.

3.4.1 Function linearization

To simplify computation, piecewise linear functions were used to substitute the nonlinear hazmat risk function in GPM model defined in Constraints (26)-(27), (31), and (33). In particular, three intervals were used in the piecewise linearization method to balance between quality of solution and computation time. The resulting optimization model can be then solved using popular MIP commercial software without invoking the search for local or global optimal solutions of a nonlinear problem. For expositional reasons, and for sake of brevity, we do not repeat the methodology details, and we invite the reader to refer to Abuobidalla et al. (2019c).

In addition to the linear functions to account risk particularly in rail transport, Constraints (34) in the model (P_3) is non-linear of the presence of the absolute term. However, we use the linearized technique available in the literature to generate an equivalent linear form. Constraints (34) can be replaced by Constraints (37)-(38) as shown below:

$$\left[p_s - \frac{\sum_{s'\in S} p_{s'}}{|S|}\right] \leq p_s^{mad} \qquad \forall s : s \in S \tag{37}$$

$$\left[\frac{\sum_{s'\in S} p_{s'}}{|S|} - p_s\right] \leq p_s^{mad} \qquad \forall s : s \in S \tag{38}$$

It should be evident that the linear inequality (37)-(38) is equivalent to Constraints (34), because if $p_s - \sum_{s'\in S} p_{s'}/|S| < 0$ then Constraints (38) ensure that $p_s^{mad} = \sum_{s'\in S} p_{s'}/|S| - p_s > 0$. Also, if $\sum_{s'\in S} p_{s'}/|S| - p_s < 0$ then Constraints (37) ensure that $p_s^{mad} = p_s - \sum_{s'\in S} p_{s'}/|S| > 0$. Hence, in both cases, the solution from linear inequality (37)-(38) will be equivalent to that from Constraints (34).

After applying the piecewise linearization process, the original optimization model $P_q, q = 1, 2$ is reduced to the mixed linear integer programming (MIP) model $P'_q, q = 3, 4$. For model (P_5), we also replace Constraints (34) by linear form as discussed above then the original optimization model is also reduced to the MIP model P'_5.

3.4.2 Heuristic search

Problem $P'_f, f = 3,4,5$ is a version of train scheduling problem with rail freight routing decisions which involves two main nested decisions; the timetable of train services, through $\tau^o_s, \tau^c_s, \tau^d_s, \tau^a_s$ variables, and the assignment of commodities to train sequences according to the timetable of train services, through $x_{k,s}$ variables. The MIP heuristic is designed to account the hierarchical nature of the considered problem. Once we decide the schedule of the candidate trains, one must extract the possible itineraries for the shipments and solve restricted multicommodity flow problem. The heuristic focuses on train schedule problem, as they influence the dimension of the solution space, by fixing a subset of the train services and then restricted car routing and scheduling problem is heuristically solved given the schedule of the train services. The procedure has two main subroutines: obtaining a feasible solution and then re-optimizing one train at a time. Detail of the heuristic is given below.

A feasible solution of the Problem $P'_q, q = 3,4,5$ is obtained by giving a fixed time limit to the MIP solver. Then, the current solution is iteratively improved by reoptimizing, with some randomness, one train at a time, we define a MIP model for the problem in which all the schedule of other trains in the solution is fixed and all the variables associated with commodities assignment of that train are present. The heuristic iteratively solves a sequence of the MIP sub-problems of the model with the subset of $x_{k,s}$ and $y_{s,s'}$ binary variables fixed. Let $R_r(s,s')$ ($R'_r(k,s)$) be the set of train services (shipment assignment) to be fixed at iteration r. The heuristic starts with an empty set in $R_r(s,s')$. Then, at any iteration r, the subset of $y_{s,s'} \backslash R_{r-1}(s,s')$ to be investigated is determined, for each train, as follows:

- By inserting in $R_r(s^*,s')$ (i.e., fixing the lower and upper bound to 0) the variable $y_{s^*,s'}$ or y_{s',s^*} $\backslash R_{r-1}(s^*,s')$ such that $y_{s',s^*} = 1$ or $y_{s^*,s'} = 1$ at iteration $r-1$ and $t^* = y^c|T|$, where $|T|$ denotes a set of trains randomly sorted, y is a random number from interval $[0,1)$, and c is a deterministic parameter ($\geq$1) that introduces some randomness.

- By inserting in $R'_r(k, s^*)$ (i.e., fixing the lower and upper bound to 0) the variable x_{k,s^*}.

The MIP is solved heuristically by limiting both the computation time and the number of nodes in the MIP solver, and the best solution is taken. Once all train services have been evaluated, the trains are reconsidered and randomly order. That is, we perform another local search by optimizing one train service at a time and solve the restricted car routing problem again. The procedure is iteratively repeated until a given amount of CPU time is exhausted or a pre-defined number of local search is achieved, whichever come first.

An extension of the above procedure is to optimize, rather than a single train, m trains in the solution and heuristically solve the MIP in which the schedule of all other trains are fixed. We consider the cases $m = 2$ and $m = 3$ to limit the computational times, $m = 1$ being explored by the procedure above. Our experimental results show that the proposed algorithm performs very well when we consider a single train at a time. Therefore, we omit the solution details when $m > 1$. The whole solution procedure was tested using several numerical examples of the HTPTDs discussed in the next section. In summary, the steps of the solution procedure are given in Algorithm 2.

Algorithm 2 *HTPTD with risk spreading heuristic*

Read data: the network information, list of request requirements, and list of candidate train services
Step 0: Reformulate the model (Section 3.4.1)
Step 1: Find a feasible solution for P'_q and update the best solution
Step 2: Randomly order the train services in T
Step 3: Apply a local search procedure by optimizing one train service at a time with some randomness and fixing all schedule of the other trains (Section 3.4.2)
Step 4: Solve restricted car routing problem given the timetable of the trains
Step 5: Update the best solution if better solution found
Go to Step 2 while the computation time is not exhausted and the number of local searches is not achieved yet
Export the best train timetabling and car routing decisions

3.5 Computational results

3.5.1 Problem setting

The algorithm procedure was implemented in C++, in particular, the MIP linear optimization was solved using Cplex v.12.7.1 and the ILOC Concert technology for building the model from the C++ language. The purpose of our computational experiment is two-fold: to demonstrate the validity of the proposed method and to compare the solution obtained for the different versions of risk spreading functions. We use two hypothetical railway networks, one in subsection 3.5.2 and the other in subsection 3.5.4. The former network, referred to as *small network*, consists of 7 terminals and 13 links. We designed 10 train journeys where each train service consists of one to three train legs. A total of 27 direct train services has been created to satisfy any request in K. The other network referred to as *large network*, composed of 15 terminals and 34 links, given in Figure 3.9. We created 25 train journeys. Each train service consists of one to four train legs. A total of 97 direct train services are available. We randomly generate demands between any pair of terminals in the network, where each node can be origin and destination for demands. For each rail routing and scheduling problem, we generate 10 independence instances and then we report the average of the performance indicators. In the *small network*, we generate 82 requests, while the *larger network* we produce 210 requests. Each customer request consists of specific characteristics including origin, destination yards, the amount of regular and hazmat materials and the available time. In the *small network*, a total of 800 railcars including 250 with hazmat railcars have to be routed and scheduled, wherein the request ranges from 6 to 16 railcars including $2-5$ with hazmat railcars. In the *larger network*, a total of 2534 railcars including 954 with hazmat railcars has been generated, wherein the request ranges from 8 to 16 railcars including $3-6$ with hazard railcars. Moreover, the cost terms were adopted from Fang et al. (2017); Verma et al. (2011). In particular, the transportation cost for regular and hazmat freight was assumed to be \$0.875 and \$1.630 per mile, respectively. The classification cost per regular freight was assumed to be \$150, whereas hazmat freight was estimated to be a 20% additional cost than the regular freight to provide safety and security requirements. The inventory cost per freight was assumed to be $50 per day.

The computational experiments were conducted on a 2.6 GHz Pentium 4 on DELL laptop with 16 GB of RAM. For the Cplex and heuristic method, we solve the problem giving a 1-hour time limit to the solver. For the *HTPTD heuristic*, we also imposed a time limit of 300 seconds for obtaining a feasible solution and 60 seconds given for the solver to solve the sub-MIP problem.

As we describe earlier, the proposed algorithm performs number of local searches over the train network; at each local search, it optimizes a single train and then we solve the restricted railcar freight routing problem. Figure 3.3 with Table 3.4 illustrates improvements in the objective function versus numbers of local searches for a rail planning problem. It show results that are fairly dramatic in the three to five moves and almost negligible after six moves. Note that move 1 represents the value of the initial solution and move 10 represents the value of final solution. Although we show the the graph for a single instance, we notice the proposed algorithm exhibit the same behavior for all instances we applied. Thus, we limit the algorithm to a maximum of 10 local searches.

Table 3.4: Number of local search vs. best objective.

Move #	1					1 – 4	4	4	4	5	5	5 – 6	6 – 8	10
Iteration	1	2	3	4	5	6 – 17	18	19	20	21	22 – 23	24 – 29	30 – 47	48 – 50
Objective	638038000	450077000	258200000	97412400	464393	357191	337203	330127	324585	302396	260576	252577	246686	243775
Improv.	–	−29.46	−42.63	−62.27	−99.52	−23.08	−5.60	−2.10	−1.68	−6.84	−13.83	−3.07	−2.33	−1.18
GAP	265749.17	187432.08	107483.33	40488.50	93.50	48.83	40.50	37.55	35.24	26.00	8.57	5.24	2.79	1.57
Time(sec.)	1.60	1.99	2.49	10.16	12.56	14.45	30.05	31.23	33.54	34.27	35.59	38.04	43.23	61.70

3.5.2 Impact of commodity type

To study the impact of the type of commodity on the final trains schedules and risk indicators, we generated four groups of instance, one consists of regular railcars (referred to as R), one contains hazmat railcars (referred to as H) and two composed of different combination of regular and hazmat railcars in request. In the R/H group of instances, more regular railcars are generated than hazmat railcars. In contrast, the H/R group of instances contains higher hazmat railcars in a request.

We report the results for the proposed heuristic in Table 3.5 together with schedule of train services in Figure 3.4-3.7. The train schedule shows how the train will move over time,

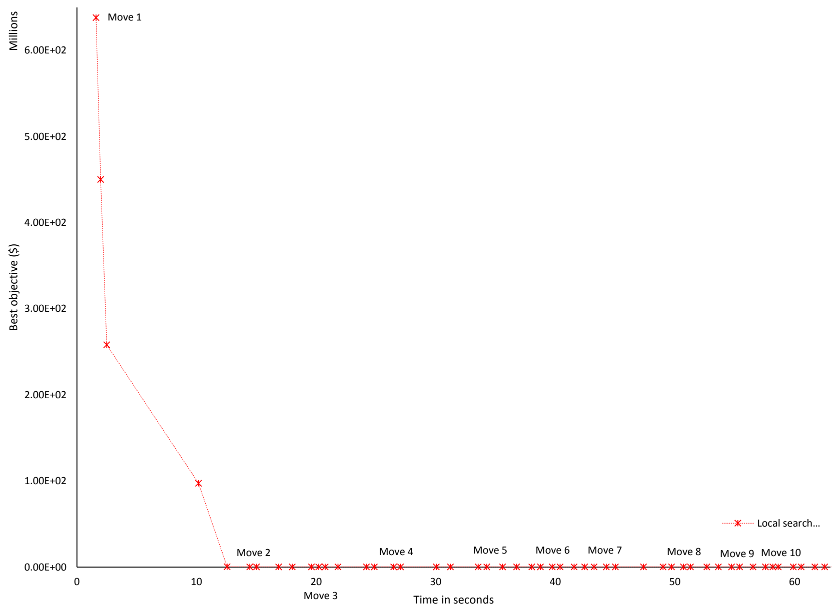


Figure 3.3: Number of local search.

Table 3.5: Type of commodity in customer request.

PI/I	$Regular(R)$	$Hazmat(H)$	$Regular/Hazmat(R/H)$	$Hazmat/Regular(H/R)$
$Load(\%)$	49.83	49.75	46.19	46.33
$N.Partner$	6/84	5/84	5/84	5/84
$T.Holding$	68.03	104.84	35.87	133.19
$T.Distance$	140479	140400	138086	135753
R/H	800/(−)	(−)/800	562/238	239/561
x^{IDLH}	−	1.33	1.19	1.11
p^{max}	−	176014	79637	227533
p^{total}	−	2317868	733484	1818107
$Obj.Init.$	80011.9	58196.7	90110.9	203191
$Obj.fin.$	58011.1	58188.2	58089.5	58169.6
$P.D.(\%)$	−27.50%	−0.01%	−35.54%	−71.37%

*The computational time for running different instances ranged from just a few seconds to 1 minute for an average model runtime of 40 second.

where the x-axis gives the time horizon (expressed in days) and the y-axis gives the terminal number in the network. The results for the four groups of instance are reported with respect to the average train utilization obtained from $Load(\%) = \sum_{k\in K}\sum_{s\in S_k}(D_k x_{k,s}/U_s)100$; the number of requests served by a partner obtained from $T.Partner = \sum_{k\in K} z_k$; the total holding times obtained from $T.Holding = \sum_{k\in K}\sum_{s\in S_k} h_{k,s}$; the total distance covered by commodities in kilometre ($T.Distance$); total regular/hazmat freights (R/H); the average IDLH from 1 (least risky) to 3 (most risky) x^{IDLH}, the maximum population exposure obtained from $p^{max} = \max_{\forall s\in S} p_s$; the total population exposure obtained from $p^{total} = \sum_{s\in S} p_s$; the initial (final) objective ($Obj.Init.(Obj.fin.)$); and the percent deviation obtained from $P.D. = (Obj.fin. - Obj.Init./Obj.Init.)100$.

From the trains schedule shown in Figure 3.4-3.7, it is evident that the portion of hazards in a request impacts the final schedule of train services in addition to the trip plans produced for demands. For instance, the schedule of train services produced in the H/R and H instances is planned to avoid any pair of trains that schedules too close (see Figure 3.5 and Figure 3.7) to distribute the risk. The train services in the H instance relatively spread over the planning horizon compared to one in R and in R/H instances. One may also observe that the total holding times for the solution produced in H and H/R instances is much higher than in those R and R/H instances, with an average percent deviation from R instance of 54.11% and 95.78%, respectively. When the volume of hazmats increases in a request, the heuristic attempts to hold some hazard railcars at some terminals to balance the risk by avoiding high risk train services. This could be achieved by adding some slack times between different train services.

Integrating train scheduling problem with the trip plan generation of hazmats process could distribute risk while constraining the risk along with the planned services to given risk thresholds. A total of 800 hazmat railcars in H instance exposes around 2317868 people (2897 people per railcar), whereas only 561 hazmat railcars in H/R instance exposes 1818107 people (3241 people per railcar). Such increases in the population exposure per railcar for H/R instance with respect to H instance (around 11.87% per hazmat) could be explained by the fact that few routing and scheduling options are available for H/R

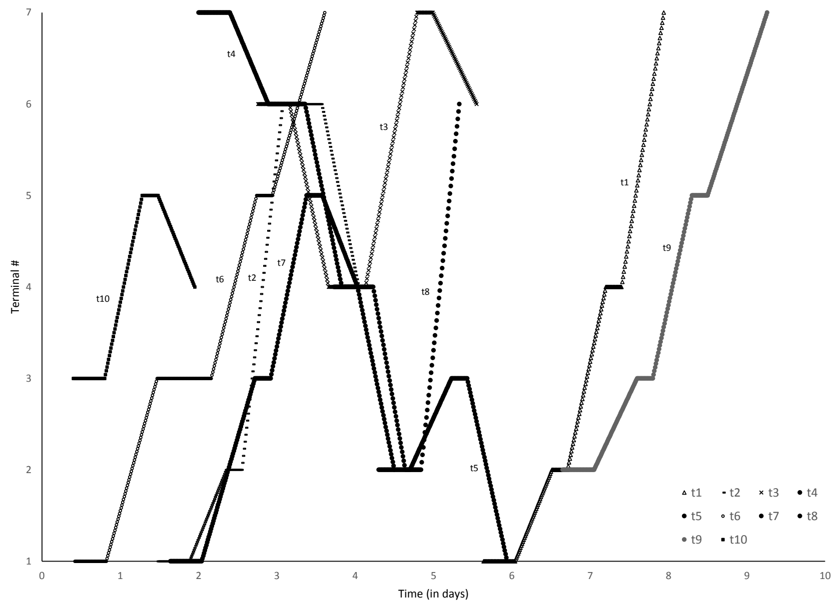


Figure 3.4: Schedule of train services (R instance).

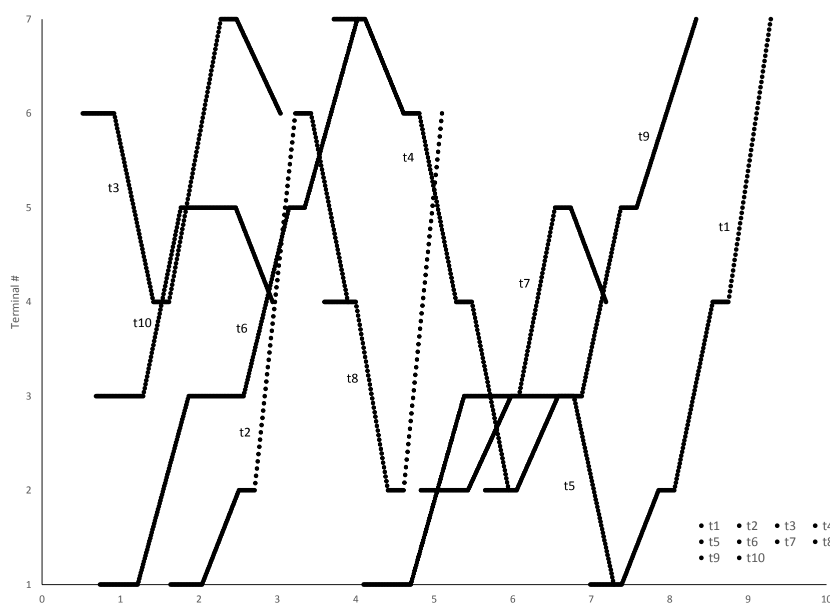


Figure 3.5: Schedule of train services (H instance).

instance given the train capacities as regular and hazard commodities shipped on the same route. One may also notice that the maximum population exposure for the H instance is around -22.64% average percent deviation from the maximum population exposure for H/R instance. This observation is consistent with previous studies on hazmat rerouting. For instance, Verma and Verter (2010) concluded that it is possible to reduce population exposure, without a significant increase in the total cost by scheduling hazmat unit-trains. Initiating hazmat unit-train not only can reduce the total population exposure but also may help in distributing risk more uniformly along with the planned services, see Bell (2006,0); Bersani et al. (2016); Hosseini and Verma (2017,1).

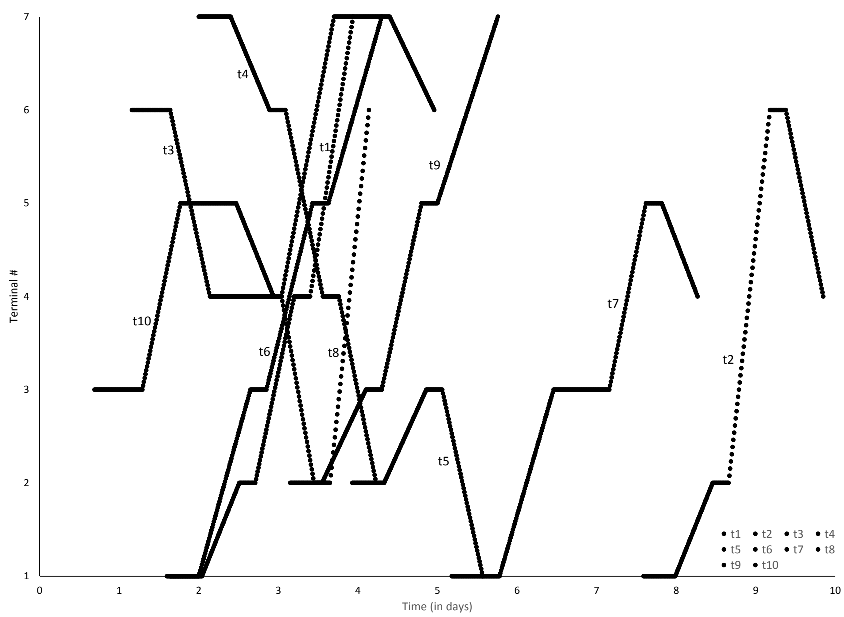


Figure 3.6: Schedule of train services (R/H instance).

3.5.3 Risk Spreading-Cost tradeoff

We generate a partial Pareto frontier for *HTPTD with risk spreading* 3 that contains the non-dominated solutions of five problem instances generated by varying the risk spreading factor ψ from 1 (point E) to 5 (point A) constituting the two extremes, given

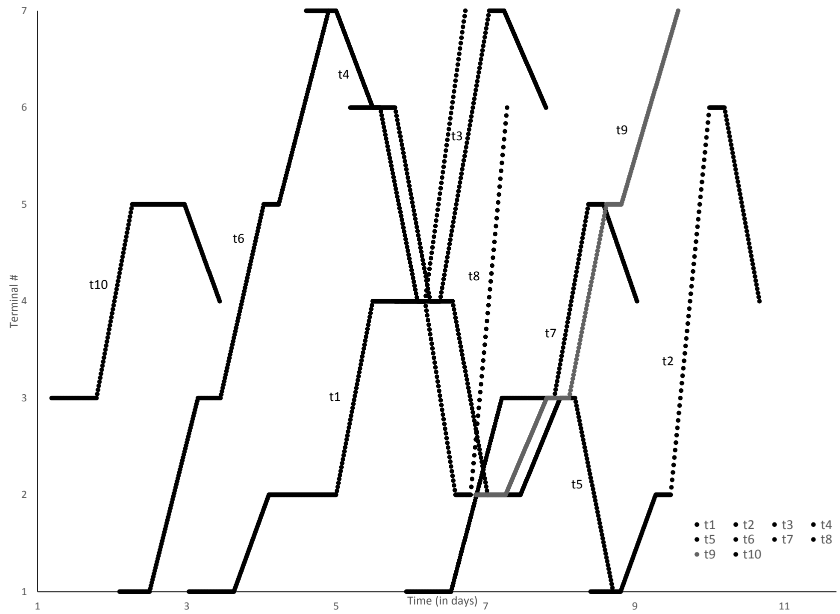


Figure 3.7: Schedule of train services (H/R instance).

in Figure 3.8. One can see the Min Cost solution (point E) entails a cost of \$93456 and produces 82318 population exposure as mean absolute deviation of the risk associated with hazmat transportation, whereas the Max Risk spreading solution (point A) will cost \$483626 and produce 14766 population exposure. The additional \$390170 could potentially improve risk spreading by 67552 (more than 82%). Perhaps a more important observation is the few improvement in risk spreading when just a significant consideration is given to risk spreading, i.e., moving from Min Cost to Max risk spreading in Figure 3.8. More specifically, an additional cost 130% (i.e., 121295) for rerouting can result in a 55% improvement in risk spreading (i.e., reduce risk spreading value from 82317 to 37251), which implies for every additional one dollar spent in rerouting hazmat freights risk spreading improve by 0.37 population exposure. It is clear from Figure 3.8 that the tradeoff along the frontier will vary in term of additional cost from rerouting the commodities against improvement in risk spreading. The benefit for improving risk spreading deceases from 0.37 (point E) to 0.01 (point A) per person.

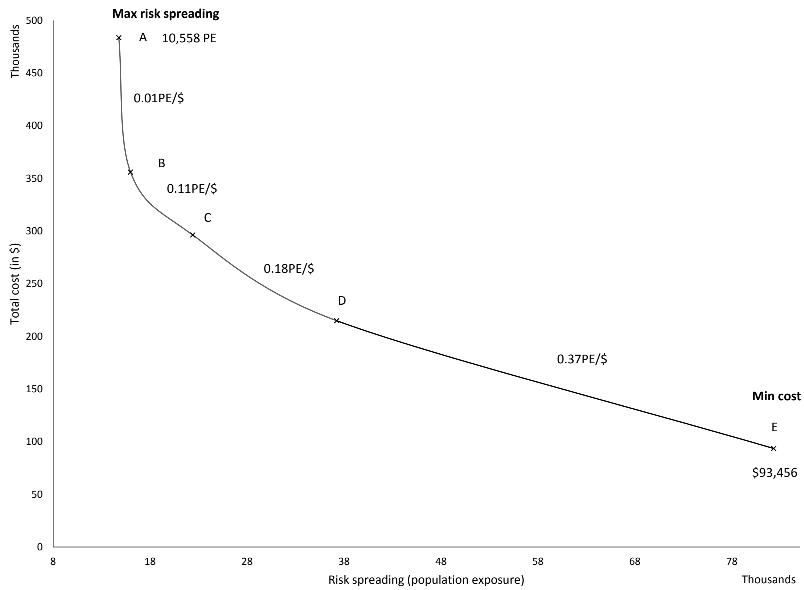


Figure 3.8: Tradeoffs between risk spreading and total costs.

3.5.4 Various considerations of risk spreading

Various risk spreading functions will most likely produce different train schedules and trip plan solutions. Table 3.6 summarizes the solutions for larger network using the proposed risk spreading strategies together with the solution obtained from the solver by limiting computation time into one hour. We divided the solutions into four parts. The first part in Table 3.6 presents the solutions regarding the total train loads, the number of commodities fulfilled by a partner, the total amount of inventory (expressed in days), the total distance traveled by commodities and the total number of commodities shipped including hazmat freights. The second part gives information on the risk with regard to the level of the immediate life and health from 1 (least risky) to 3 (most risky), the maximum population exposure (in people), the total population exposure (in people), the sum of absolute deviation and the average population exposure $p^{avg.} = \sum_s p_s/|S|$. The third part gives the average (standard deviation) of the number of services per train sequence, the average holding times per request and the average number of train changes, and the number of trains that deviate from their initial schedule. The last part in Table 3.6 presents the initial and final value of the objective function of the proposed method with the percent deviation from the initial solution as described earlier.

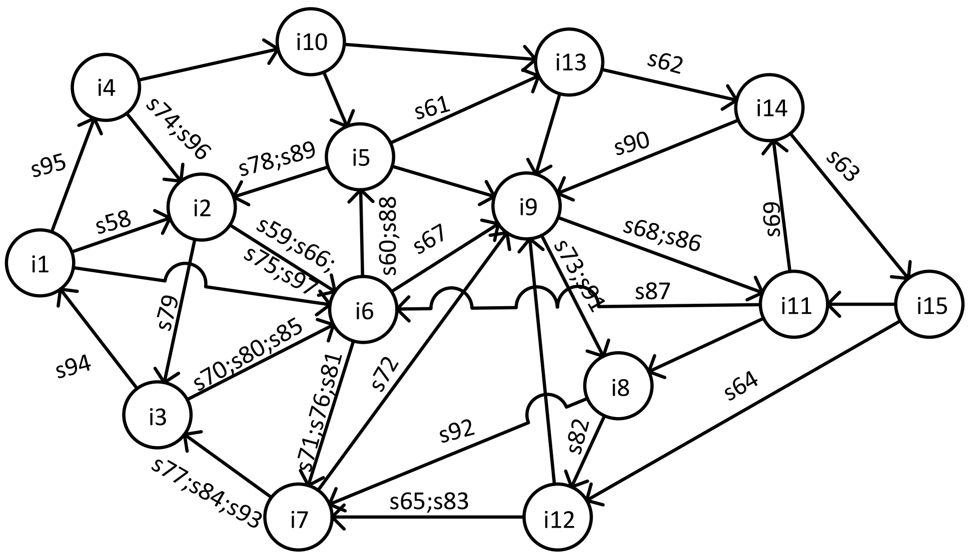


Figure 3.9: Hypothetical railway network.

To analysis the trip plan produced by the heuristic, we proposed an extension of the standard k-shortest path algorithm to generate a comprehensive list of alternative itineraries for each solution produced by the risk spreading strategy. Table 3.7 gives the total number of train sequences and average (standard deviation) number of services per train sequence for each risk spreading strategy. One may note a total of 9995 alternative itineraries are produced in the $HTPTD$ *with risk spreading* 3, with average increases of 60.92% from the one in $HTPTD$ without considering risk spreading function (6211 possible train sequences). For each demand, we create two lists of alternative itineraries, one ranked with respect to arrival time at destination and the other one with regard to distance (increasing order). We also notice that there are more than 150 alternative itineraries for some requests when risk spreading function is incorporated into the trip plan generation process.

It is obvious from Table 3.6 that integrating risk spreading functions into trip plan

Table 3.6: Performance of the proposed heuristic vs. Cplex solution.

PI/S	$Cplex^{*}$	$HTPTD^{**}$ *with risk spreading* 1	$HTPTD^{**}$ *without risk spreading*	$HTPTD^{**}$ *with risk spreading* 2	$HTPTD^{**}$ *with risk spreading* 3	$GAP1(\%)$	$GAP2(\%)$	$GAP3(\%)$	$GAP4(\%)$
$Load(\%)$	37.90	43.63	42.78	43.37	59.65	15.12	11.19	12.79	57.38
$N.Partner$	27/210	14/210	14/210	15/210	14/210	–	–	–	
$T.Holding$	98.07	96.55	56.18	137.03	235.84	−1.55	−42.71	39.73	140.48
$T.Distance$	461509	536715	519751	528331	728536	16.30	10.85	12.86	257.85
R/H	1375/824	1469/882	1453/885	1474/876	1483/890	6.91	5.91	6.46	7.91
x^{IDLH}	1.00	1.01	1.15	0.85	0.95	0.96	15.31	−13.39	−5.00
p^{max}	141262	187076	192096	157516	243651	22.43	22.17	8.46	72.48
p^{total}	3320537	4641570	4294673	4265204	4505899	39.78	20.99	22.00	35.69
p^{mad}	2542720	3889454	3461033	3334916	3000377	52.95	36.11	31.15	17.99
$p^{avg.}$	34232	47851	44275	43971	46452	39.78	29.34	28.45	35.69
$N.S.$	–	2.96(1.42)	2.90(1.36)	2.94(1.47)	3.76(2.08)	–	–	–	–
$I.$	–	0.49(0.87)	0.29(0.60)	0.70(1.03)	1.20(1.77)	–	–	–	–
$S.C.$	–	1.27(1.13)	1.15(1.04)	1.41(1.14)	1.72(1.32)	–	–	–	–
$T.C.$	–	14/25	14/25	14/25	18/25	–	–	–	–
$Obj.Init.$	–	2356050	1772020	2367030	2521000	–	–	–	–
$Obj.fin.$	270004	183233	183044	196210	175721	−32.14	−32.21	−27.33	−34.91
$P.D.(\%)$	–	−92.22%	−89.67%	−91.71%	−93.03	–	–	–	–

*The computational time for running different instances exceed 1 hour.

**The computational time for running different instances ranged from just a few minutes to 15 minute for an average model runtime of 10 minutes.

Table 3.7: Characteristics of the trains sequences.

PI/S	$HTPTD$ *with risk spreading* 1	$HTPTD$ *without risk spreading*	$HTPTD$ *with risk spreading* 2	$HTPTD$ *with risk sperading* 3
$\#T.S.$	7118	6211	8446	9995
$\#N.S.$	4.75(1.70)	5.29(1.86)	5.75(2.11)	5.25(1.78)

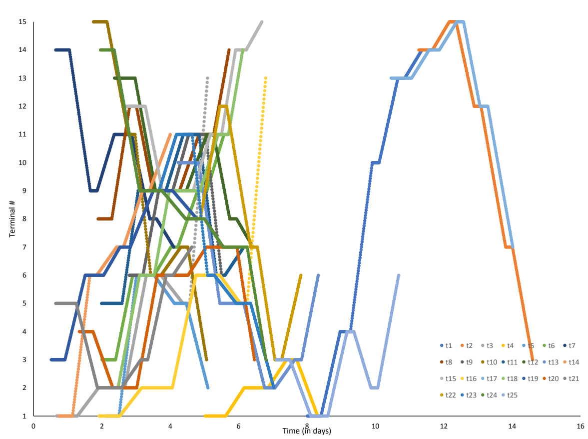


Figure 3.10: *Cplex* solution within 1 hour.

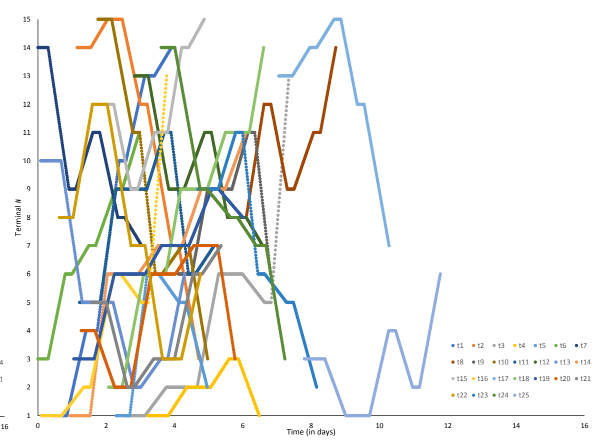


Figure 3.11: Proposed heuristic.

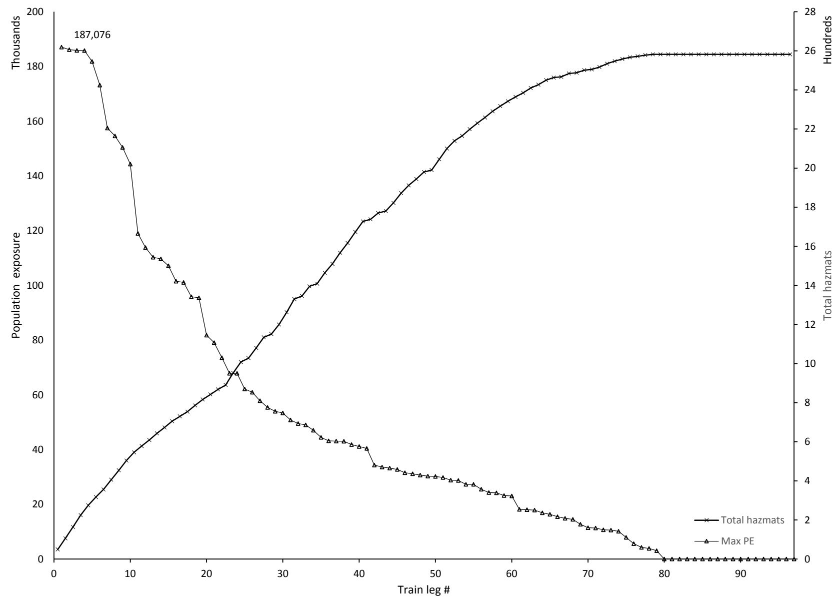


Figure 3.12: HTPTD with risk spreading 1.

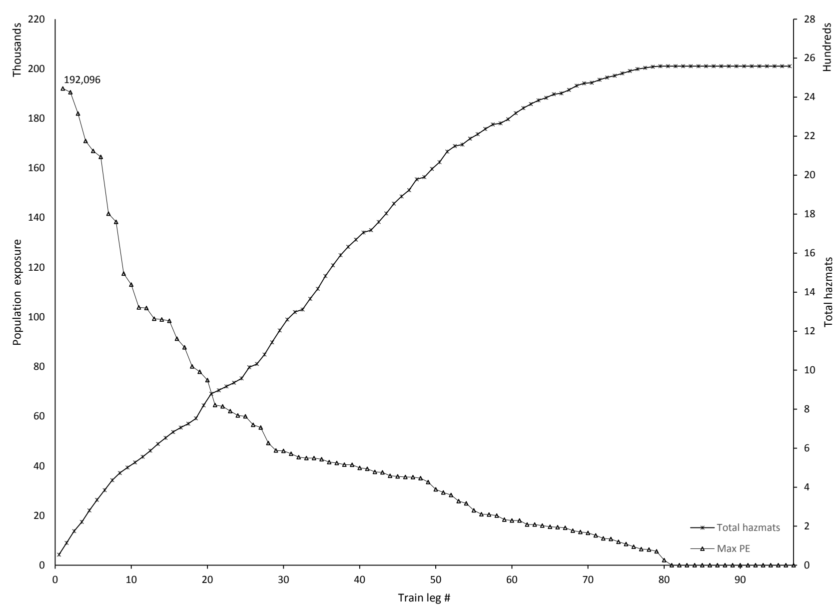


Figure 3.13: HTPTD without risk spreading.

Table 3.8: Characteristics of the trip plans.

PI/S	$HTPTD$ *with risk spreading* 1	$HTPTD$ *without risk spreading*	$HTPTD$ *with risk spreading* 2	$HTPTD$ *with risk spreading* 3
$Rank(time)$	2.34(3.71)	1.73(3.32)	4.19(6.45)	15.73(25.91)
$Rank(distance)$	4.84(0.13)	2.20(0.10)	10.03(0.27)	50.65(0.85)
$Req.(time)$	62/196	30/196	95/195	167/196
$Req.(distance)$	37/196	14/196	43/195	98/196

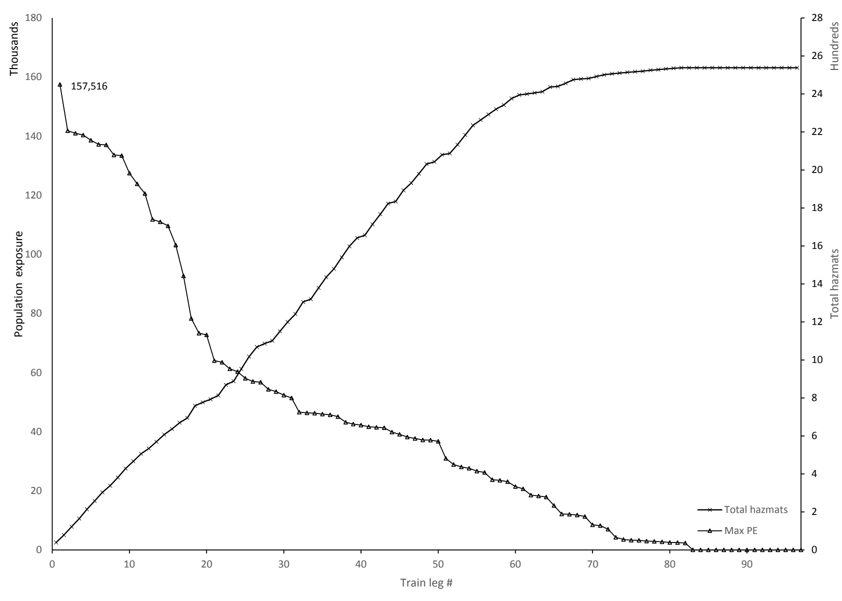


Figure 3.14: HTPTD with risk spreading 2.

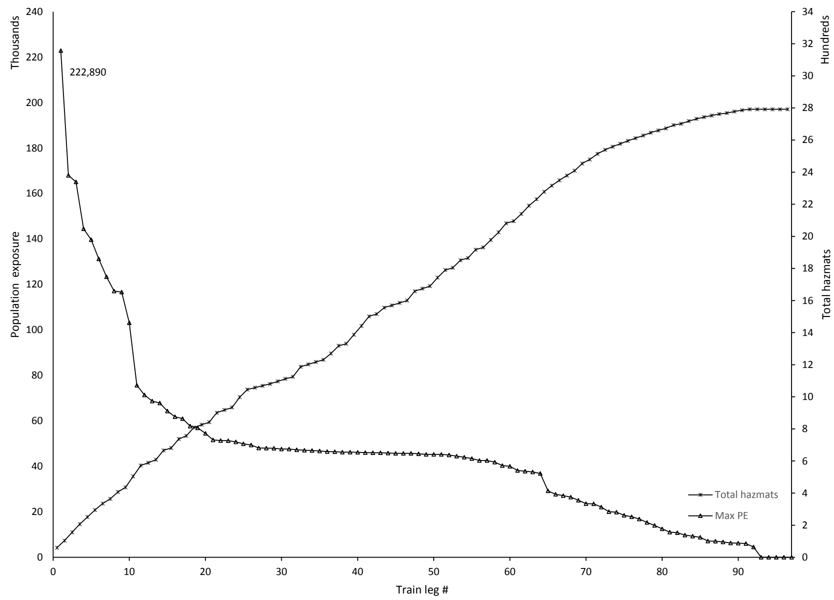


Figure 3.15: HTPTD with risk spreading 3.

generation and train scheduling decision-making process may not only increase the operational costs to the carrier but also may increase the total risks. The amount of holding times increases for the commodities in the risk spreading strategies over the *HTPTD without risk sperading* by 71.85-180.38%. To a analysis the solutions produced, we divide the requests into four groups for each proposed strategies regarding the amount of waiting times given by Figure 3.17. We can observe that 14-29% of the requests in risk spreading strategies spends more than 1.5 days in holding status. Figure 3.18 depicts the percent of each operation, either moving, sorting, waiting or holding, for a commodity along its itinerary, where we can see that a commodity being on holding status not less than 19% of the time. This increase could result from the fact that some commodities deviated from the shortest itinerary to balance the risk, causing delays for some non-hazmat demands to accompany the hazards on the same train services. Allowing the hazmat shipments to be temporary stored at some terminals along their itineraries can be an effective strategy to spread the risk, assuming there is zero risk from holding hazmat at terminals.

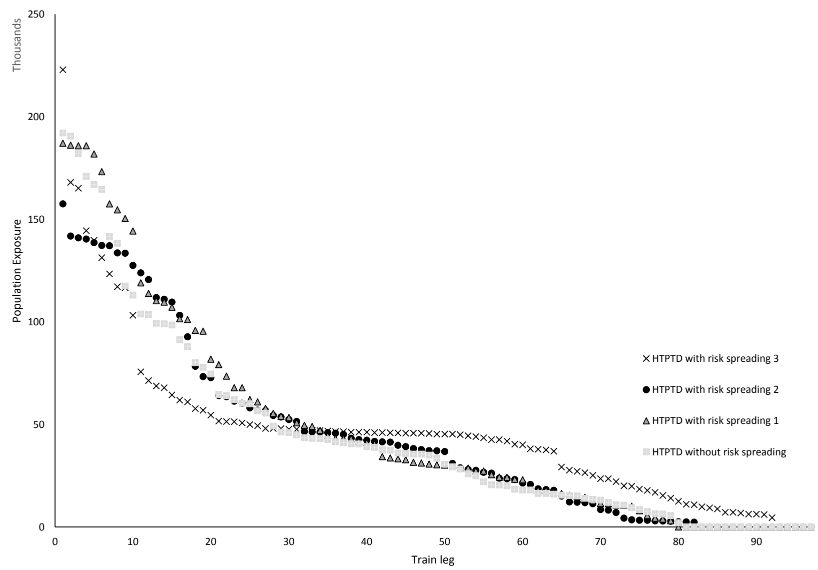


Figure 3.16: Population exposure per train leg.

Table 3.8 gives the characteristic of the generated trip plans for each proposed strategy. In the first part of Table 3.8 presents the average (standard deviation) gaps, whereas the second part gives the number of commodities deviated from the shortest itinerary with respect to time and distance, respectively. For instance, without considering risk spreading most commodities follow the 2nd or shortest itinerary (time) and the average increases in distance is not more than 2.20% from the shortest itinerary (distance). In the case when the decision maker incorporate risk spreading into trip plan generation, some requests shipped along the 3rd-16th shortest itinerary (time) and the average increases in distance varies from 4.84 to 50.65% from the shortest itinerary (distance). In most cases, hazmat shipments likely affect rail operations. Rerouting of hazardous materials train to distribute the transport risk may increase mileage and in-transit time for non-hazmat commodities on the same train.

It is also evident that the percent deviation from the shortest path varies from one risk spreading strategy to another. For example, *HTPTD with risk spreading* 3 strategy causes

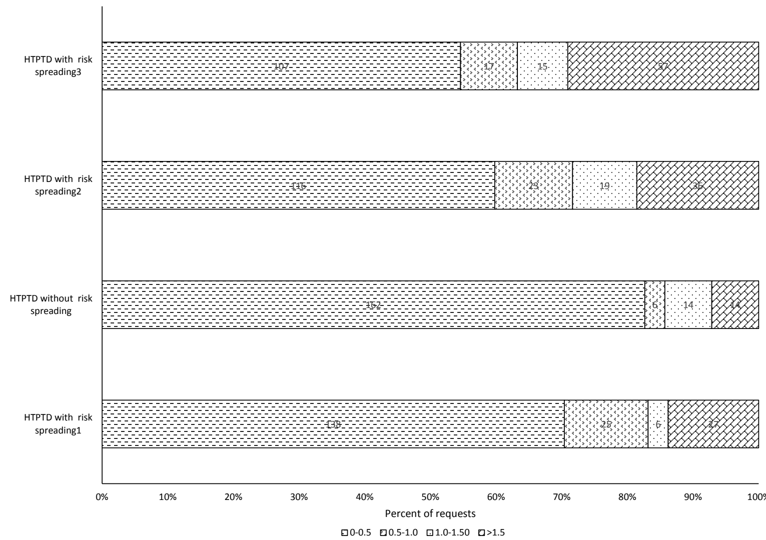


Figure 3.17: Holding time vs. HTPTD strategies.

the largest mean deviation from the shortest itinerary compared to the other risk spreading strategies. $HTPTD$ *with risk spreading* 3 strategy attempts at balancing the risk among train services rather than minimizing the maximum or difference between the maximum and minimum population exposure. To study the impact of various risk spreading quantities on the trip plan generation process, we classified the train services into four groups based on the total population exposure, (a) most risky $level1 = \{s \in S : p_s > 100,000\}$; (b) moderate risk $level2 = \{s \in S : 50,000 < p_s \leq 100,000\}$; (c) low risk $level3 = \{s \in S : 0 < p_s \leq 50,000\}$; and (d) zero risk. Figure 3.19 together with Figure 3.12-3.15 depicts the percentage of exposure levels for each risk spreading strategy and without risk spreading considerations. It is obvious that the number of services in $level1$ and $level4$ for $HTPTD$ *with risk spreading* 3, 5 out of 97, is the least among the other risk spreading strategies. Whereas the other two risk spreading strategies reduce the maximum and difference between the maximum and minimum population exposure by shifting hazmat railcars between services in $level1$. This shows that the maximum or the difference between the maximum and the minimum transport risk may not lead to balance risk distribution among the population, not less than 18%

of train services with zero risk (see Figure 3.16). When some train services supports the transport of a high volume of hazmat, the maximum risk in the network will be defined by these train services and the other train services become unimportant in spreading the risk (see Figure 3.12 and Figure 3.14). It is simply shift the transport risk from one train leg to other train legs. Thus, the maximum population exposure or the different between the maximum and the minimum population exposure may not lead to fairly distribute the risk over the population.

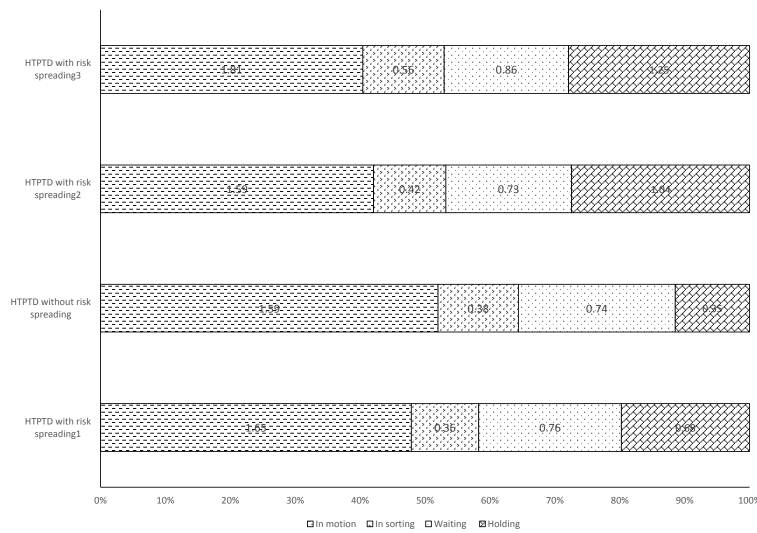


Figure 3.18: Percent of operations.

Different than minimizing the maximum or difference between the maximum and minimum population exposure, *HTPTD with risk sperading* 3 calculates a global measure to distribute risk more equitable, by avoiding overloading any railway service or part of the network. As a result, some shipments shipped along longer itineraries to balance the risk among the train services (3.76 vs. 2.90 train services). Since some requests considerably deviates from the shortest itinerary from rerouting the hazardous materials, the total risk increases by 39.78%. The population area with a low risk will be penalized from the risk spreading, i.e., 5 out of 97 for *HTPTD with risk sperading* 3. This new definition of risk spreading allow us to generate similar routes that do not share common train services. Considering risk spreading function into trip plan generation may not only have to incur an unbearable financial cost to the carrier but also may increase the total risk, which could be undesirable from a carrier's perspective. Following Fontaine et al. (2016), one may incorporate the total transport risk to the carrier's objective function to avoid significant increase in the total population exposure while spreading the transport risk over the population.

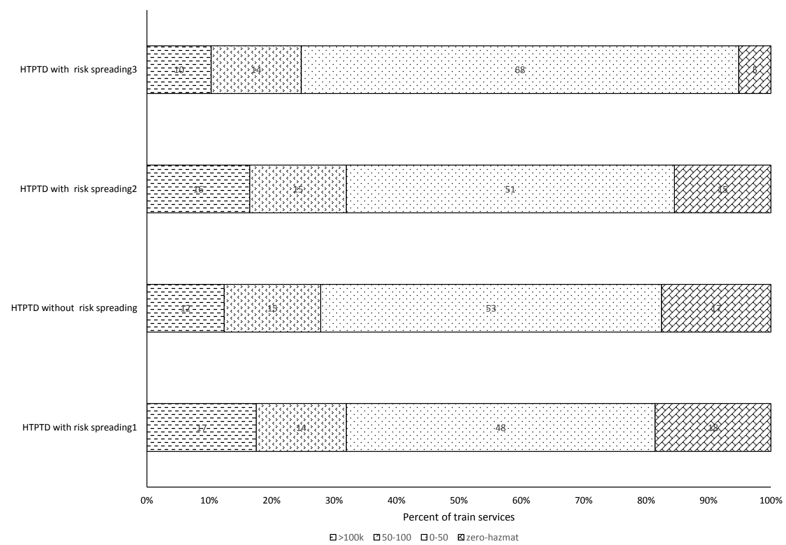


Figure 3.19: Risk class.

Distributing risk over the railway network is a feature attractive to railway operators for balancing risk and planning emergency response teams. Integrating risk spreading function into the trip plan generation process helps in mitigating the adverse impacts of accidents/derailments when they happen. To comply with risk spreading requirements, resources allocation of the hazardous materials response teams must be allocated with spatial equity to avoid zone with an abnormally low possibility of derailment with high consequence (Garrido, 2010). The additional operational costs can be added to the shipping charges by quantifying most cost factors from incorporating risk spreading function into trip plan generation process. Of course, the operator must be very cautious in estimating the additional shipping costs to avoid causing a substantial shift in hazardous materials shipments from railway to truck, which might increase overall transport risks as trucks are more prone to accidents than are railcars (Bagheri et al., 2014).

3.6 Conclusion

In this chapter, we model the planning and scheduling of hazmat freight problem with train scheduling decisions while taking into accounts risk distribution function. A heuristic method has been designed to solve a realistic size problem instances. The experiment results revealed that considering risk distribution function into trip plan generation may not only have to incur unbearable financial costs to the carrier but also increases the total risk, which it could be undesirable from a carrier's perspective. In particular, some requests considerably deviated from the shortest path with an average of 16.29%, causing increases in the total risks by 39.78%. We also show that the carrier can achieve a high level of risk distribution by integrating train scheduling decisions into trip plan generation process. More precisely, the waiting of commodities at some terminals represent the opportunity of demands flows to be temporarily stored at some terminals along their itinerary, to be picked up by less risky train services passing by at later times to meet safety regulations. This could be achieved by adding some slack times between different train services. The additional operational costs can be added to the shipping charges by quantifying most cost factors from incorporating risk spreading function into trip plan generation process.

Chapter 4

Modeling and solution method for HTPs with pricing decisions

Integrated Hazardous Materials Trip Plan Problem and Pricing Decisions for Railway Supply Chain System

Omar A. Abuobidalla, Mingyuan Chen, Satyaveer S. Chauhan

This manuscript is under review in Research in Transportation Business & Management (August 2019)

In this chapter, a rail freight transportation planning problem to ship regular and hazardous materials is studied. An optimization-based approach is used to assign the incoming railway requests to the best available itineraries while satisfying the capacities and risk thresholds of the planned services. The planning procedure consists of two phases. In the first phase, a deterministic freight transportation problem with train scheduling decisions is modeled and solved for shipping freight commodities known in advance. The solution determines the schedules of train services and the best demand-itinerary assignment decisions. In the second phase, real-time planning of hazmat problem is built and solved at the arrival of the new requests. Numerical examples are provided to illustrate the considered problem and the proposed solution method.

4.1 Introduction

Making the best allocation of limited resources, while meeting customers commitment times and price quotations, is a common challenge in many industries including railway transportation providers. To address this challenge, rail carriers are continuously under pressure to develop an optimization-based tool to answer their customer's requests in real-time (Törnquist, 2006) while taking into account the current status of the railway network. In practice, customer requests for a railway move are not known in advance (Crainic, 2000). A subset of the request's information is gradually revealed over time. The operator may adapt the assignment of the specific commodity to another train sequences as new information is revealed, aiming at releasing some loads for specific train services to accommodate future in demands (Cao et al., 2012). There is no doubt that the advances in information and communication technologies, such as advanced train control system, have provided railway operators an opportunity to automate their operation process (Kraay and Harker, 1995) while considering the risk from transporting hazmats (Verma et al., 2011) and the revenue generated from serving demands (Crevier et al., 2012).

Railway carriers transport a large volume of hazardous materials in addition to transporting regular freights. According to recent statistics in 2012, rail companies shipped almost 111 million tons of hazmats in the United States (DOT, 2017b) and 26 million tons of hazmats in Canada (Searag et al., 2015). In North America, chlorine and ammonia are frequently shipped in railway services that become airborne in the event of an accidental release (Branscomb et al., 2010). Chlorine is mainly used for purifying potable and wastewater and also used in as chemical intermediary in different industries, for goods ranging from PV pipes to shampoo. Ammonia is a commercial fertilizer and mainly used in agricultural farms. The impact potentially harmful to human health and environment, in case of derailment or accident causing hazmat releases, is quite large. Since some of the hazmat trains are routinely routed near the urban areas, train accidents or derailments pose a significant security threat. The rail disaster in Lac-Mégantic, Quebec, resulted in 47 fatalities in 2013, is an example of low-probability high-consequence (LPHC) event. Railway transportation of hazmats, including Toxic Inhalation Hazard (TIH), is crucial to economy supporting the national supply chain despite the safety and security concerns associated with transportation of hazardous materials.

Traditional hazmat trip plan problems ignore the revenues generated from serving the requests and focus on costs resulting from routing and scheduling the demands. Following *the Common Carrier Obligation* in North America, the carriers are prohibited from refusing shipment of dangerous cargo (Roberts, 1978). In general, this requirement expresses the implicit hypothesis that the total costs from rerouting hazmat commodities will be compensated by the total revenue generated. Such an assumption does not necessarily hold, and incorporating pricing decisions have important implications in the total net profits obtained (Crevier et al., 2012) and population exposure as well (Bianco et al., 2012). In most cases, hazmat shipments likely affect rail operations. Rerouting of hazardous materials train to avoid populated areas may increase mileage and in-transit time for non-hazmat commodities shipped on the same train. Accordingly, the carrier may modify their pricing strategies to compensate the increases in the operating cost and transport risks (Marcotte et al., 2009).

4.2 Related literature

Since the proposed study related to multiple sub-areas within the transportation domain, we organized the literature review into three groups: Routing and scheduling of hazmat; Real-time routing and scheduling; and Revenue management and pricing decisions.

Routing and scheduling of hazmat: A majority of the literature on hazmat routing and scheduling problems is devoted to road transportations (Bianco et al., 2009; Erkut and Alp, 2007b; Nozick et al., 1997a; Verter and Kara, 2008) as transportation by trucking companies account for a large percentage of hazmat shipments, while research in railway transportation of hazmat is comparably less (Erkut, 1995; Erkut et al., 2007; List et al., 1991). Over the past three decades, many mathematical models and solution methods have been proposed to tackle various aspects of railway transportation of hazmat problems such as: (a) Risk assessment (Verma and Verter, 2007); (b) Network design (Reilly et al., 2012);

(c) Routing (Glickman et al., 2007; Verma et al., 2011); (d) Routing and scheduling (Fang et al., 2017); (e) Train makeup (Bagheri et al., 2011; Cheng et al., 2017); (f) Routing and location (Romero et al., 2016); (g) Blocking, train makeup, and rail freight transportation (Abuobidalla et al., 2019c), (h) Toll setting (Assadipour et al., 2016), among others. Since all the input data of the hazmat routing problems are considered known in advance before the routes are built, most models in the hazmat transportation literature are developed to solve *static routing* problems. In a *dynamic routing* problem, some of the demands are gradually revealed over time, and the operator may modify commodity-itinerary assignment decisions. The prevailing studies on hazmat transportation literature can be classified into three groups. The first group known as *a priori optimization*, the optimized routes (and schedules) are determined before the travel starts. An update on the routing (and scheduling) decisions en-route will not be performed. In the second group known as *adaptive route selection*, the decision-maker frequently collects new information that may be used in improving routing decisions. The optimized route depends on the intermediate information concerning past travel times and/or weather conditions. In the last group known as *adaptive routing and real-time updates*, the optimized routes might be changed en-route due to real-time updates of the information and followed by re-optimization procedure (Beroggi, 1994; Koutsopoulos and Xu, 1993). Erkut et al. (2007) observed that most literature on hazmat transportation focuses on the static version and few studies dedicated to adaptive routing decision.

Real-time routing and scheduling: A commonly used strategy for solving a dynamic routing problem is to adopt an algorithm that repetitively solves the static version of the problem. Each time new information is revealed, for instance a new request arrives, a static model is built and solved. The algorithm may need to modify some inputs to ensure the solution is feasible concerning past decisions. A drawback of such an approach is that one must perform re-optimization when new information is revealed and may be time-consuming to be solved in real-time. To work around that one may restrict the number of requests at each re-optimization problem (Goel, 2010; Yang et al., 2004) and/or explicitly consider the time when a decision must be fixed, referred to as response time (Tjokroamidjojo et al., 2006; Zolfagharinia and Haughton, 2014,1). In railway transportation, the response time can be interpreted as the time in which the operator gives his/her best and final offer regarding delivery and price quotations for their customers. The operational planning literature can be grouped into two groups: Resources planning and Itinerary replanning. Resources planning problems focus on the allocation of all resources throughout the network including positioning, repositioning, holding, and assigning them to customers (SteadieSeifi et al., 2014). Itinerary replanning problems deal with real-time optimization of schedules and routing decisions. Resource planning and itinerary replanning are often interrelated and could be solved together under a comprehensive operational planning problem (Bock, 2010; Özdamar et al., 2004).

Revenue management: Integrating revenue management issues into daily planning decisions becomes more and more important in intermodal industry (Li and Tayur, 2005), railway companies (You, 2008), maritime transportation (Maragos, 1994), trucking companies (Powell et al., 1988) and airline transportation (Côté et al., 2003). Armstrong and Meissner (2010) provide an overview of railroad revenue management for passenger and rail freight transportation, and Gorman (2015) discusses revenue management in U.S. railway systems. Various pricing strategies have been tailored to address revenue management in railway transport. In using *Service-Based Pricing strategy*, different service levels are created to satisfy various customer requirements. Segmenting customers and charging different tariffs for different segments, may be better utilized the capacity of the train services (Kwon et al., 1998) and also may help in reducing the risk associated with hazmat shipments (Bianco et al., 2012; Marcotte et al., 2009). These segments can be identified based on differentiating the service levels (premium or regular deliveries), types in terms of order placement (advance or late booking) and types of commodities to be shipped (hazmat and non-hazmat). Kraft (2002) showed that differentiating service level while satisfying customer requirements may be less costly than adding more capacity and considered as a routing and scheduling problem. The problem was decomposed into a static trip planning problem with accepted known requests and a dynamic trip planning problem with unknown requests. In practice, railway companies accept customer requests as long as free capacity exists (Campbell, 1996), and the pricing decisions are often decided according to the actual cost to fulfill the demand plus profit margin (Jarocka, 2016; Tretheway and Waters, 1993), i.e., the intermediate activities for serving the demand. When railway services face scarce resources, premium demands may be denied due to infeasibility (Bilegan et al., 2015). Crevier et al. (2012) proposed a bi-level mathematical formulation integrated pricing and rail freight transportation decisions considering the blocking, routing, train makeup, and scheduling plans. They studied two pricing strategies: disjoint pricing and common pricing. Another possible revenue management strategy, known as *dynamic capacity allocation*, is to hold the capacities of some vehicles for late customers call in, provided the freight is sufficiently profitable (Pak and Dekker, 2004). In most cases, those strategies are modeled as probabilistic mixed-integer programming on a space-time network of the transportation services with some probabilistic knowledge of the future requests (Bilegan et al., 2015; van Riessen et al., 2017; Wang et al., 2016). For many years, consolidated-services industries recognized that revenue management tools can optimize service operations by tailoring service level and prices to a certain group of customers.

As can be seen from the literature, the study on integrated pricing decisions and hazmat trip plan problem in railway transportation is limited. As noted by Branscomb et al. (2012), the railway carriers tariff is not adequately reflected the risks associated with hazmat transportation. In this chapter, we consider a freight car scheduling and train dispatching problem involving hazmat transportation. In the considered problem, customer requests known in advance will be scheduled first. Additional requests, after the preliminary schedule is generated, may be accepted from new customers. Depending on available capacities, the increases in transport risk and the generated schedule, new customers may be quoted with different prices and time to deliver. A two-phase heuristic solution method is developed to solve the considered problem. In the first phase, we solve integrated train timetabling and deterministic freight transportation problem for the known requests in advance. The solution determines the timetables of the train services and best demand-itinerary assignment decisions. In the second phase, a real-time optimization problem is built and solved at the arrivals of new freight requests. In this work, flexibility was introduced by re-optimizing the freight-to-itinerary decisions several times in sequential request arrival. In some cases, adding the demand to the current train services is feasible and profitable as only additional fuel and equipment are needed. In other cases, the existing itineraries may need to be revised causing the increased cost of transporting the already existing scheduled freights. Or, some of the new requests must be rejected as it becomes infeasible. Numerical examples are provided and managerial insights are drawn. The analytical analysis allows railway managers to gain insight into the risk-revenue tradeoff in routing hazmat and also helps the management to decide delivery and price quotations for the additional demands considering risks associated with hazardous materials. Details of the considered problem and the proposed solution methodology will be presented next.

The chapter is organized as follows. The considered problem is defined in section 4.3. The real-time methodology is described in section 4.4. Numerical examples are provided in section 4.5 to illustrate the considered problem. Finally, we conclude our research and provide possible research directions in section 4.6.

4.3 Problem Statement

The general problem of hazardous materials trip planning with train scheduling decisions is described first and then the problem of allocating the incoming requests to train sequences with pricing decisions is discussed. The associated notation is identified as well. Hereafter, we refer to the first problem as *hazardous materials trip plan problem with train scheduling decisions* (HTPTD) and the second problem as *hazardous materials trip plan problem with pricing decisions* (HTPP).

4.3.1 Problem characterization

Discussions for both problems will be presented here since they are closely related to one another, as well as to previously published in literature (Cao et al., 2012; Kraft, 2002; Wang et al., 2016) among others, and it is important to understand both the similarities and differences between the two rail freight transportation planning problems. Although the solution procedure for HTPTD will not be discussed here in details, computational experiments result will be presented later.

A railway operator is in charge to manage various customer requests for carload moves within a railway network. Although the operator knows some information about customer demands currently processed or previously scheduled, there exists a great deal of uncertainty in future demands as new requests may arise in midst of operation. The operator may revise the schedule of already scheduled demands in order to reduce the capacities on a certain train services or transport risks associated with hazardous materials. Existing literature suggests that the railroad shipment routing and scheduling problems might be decomposed into two nested subproblems, a deterministic HTPTD process for demands known in advance (traditional customers) and a real-time HTPP process for future and unknown demands (irregular customers) in which delivery and price quotations have not yet been decided.

The two problems are interrelated since if train services are fully reserved or delivery quotations are very tight, then the HTPP process will not able to accommodate irregular demands. To avoid such situation, the two problems must be linked through either joined capacity (i.e. Cao et al., 2012; Liu and Yang, 2015) and risk thresholds constraints or optimized by a single model (i.e. Wang et al., 2016). The advantage of the former method is that it requires less memory to record decision parameters, and also computational efforts are usually not expensive. The advantage of the latter method is that it obtains optimum solution, and their weakness is that it imposes a limitation on solving large railway planning problem. To deal with the railcar routing and scheduling problems face in practice, we adopt the former method to solve the considered problem. The solution of the HTPTD determines, for each train service, arrival and departure times in the terminals of the railway and freight-to-train decisions. The solution for the HTPP gives, for each irregular request, the delivery and price quotations and the sequence of train services that demand will follow (if served) while creating the minimum rescheduling for the already existing scheduled demands without breaking their delivery and price quotations. Indeed, the HTPTD model is a general formulation of the HTPP model. These two problems are sufficiently distinct in required inputs, outputs, and solution time to justify different solution methods, even through formulations are very close to another.

Accordingly, we introduce different categories of customers with the definition of specific treatment for each of them, including accept/reject basis and particular delivery and price regulations. In particular, we grouped customer requests into two classes as follows: (a) *traditional customers*, who sign long term contracts with the carrier, must be fulfilled by the carrier's own services, and their delivery and price quotations are set in advance and not subject to change; and (b) *irregular customers*, who make request for a carload moves less frequently and on an irregular basis, maybe outsourced/rejected because of (1) lack of train capacities, (2) additional risk exceeds the given risk thresholds, or (3) service level requirements. Their delivery and price quotations are determined according to number of factors including the remaining train capacities and risk thresholds at the time of decision. Table 4.1 gives the main characteristics of traditional and irregular demands (illustrated in Figure 4.1).

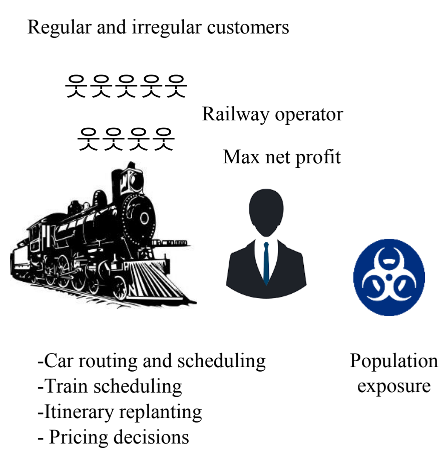


Figure 4.1: Schematic diagram of the HTPs with pricing decisions.

Railway companies often provided their clients with service and price quotations according to the transportation plan with some additional surcharges and slack time are added to handle daily operational variability (DOT, 2017a). Pricing quotations developed by many

Table 4.1: Characteristics of traditional and irregular request.

Charac./Request	*Traditional*	*Irregular*
Information at $t=0$	*known*	*unknown*
Tariff/Price	*fixed*	*dynamic**
Reject	*no*	*yes*
Initial trip plan	*yes*	–
Request – Itinerary	*dynamic*	*dynamic*
Deviation in delivery	*not allowed*	*not allowed*

*determines based on the additional train loads and risk.

railroad companies are most often established by adding a profit margin to the actual cost (Li et al., 2015). For example, Canadian National (CN) Railway Company developed pricing and service quotation's guideline for their customers (CN, 2019) give the customers with general expectation about level of service and estimation of shipping costs to serve their demands, as they are not established on a customer-by-customer basis and do not consider the real-time status of the railway into consideration.

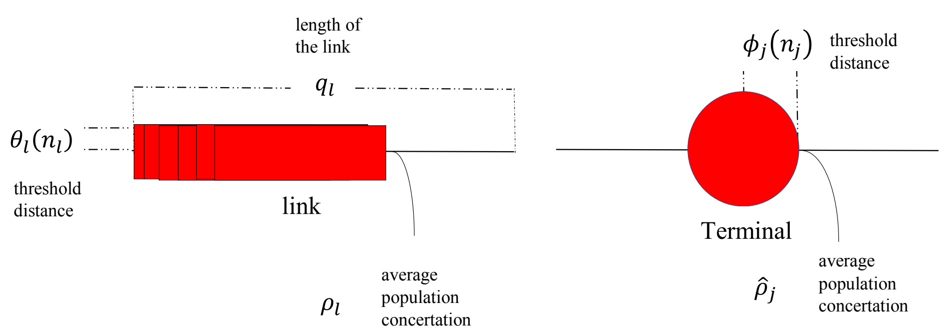


Figure 4.2: Danger rectangular and circle.

In compliance with the railway policy and government regulation, the operator evaluates the risk associated with hazmat transportation when generating trip plans aiming at limiting the public risk below the given risk thresholds. While there is no universal expression on how the hazmat transport risk might be stated, almost all researchers adopted either the accident probabilities or an estimate of the consequences, or both (Erkut and Verter, 1998). As most railway operators exhibit risk-averse when transporting hazmats that may cause high consequence (Bell, 2007), most researchers focus on the consequence in evaluating the risk (Verma et al., 2011; Zhao and Verter, 2015). In this work, the most popular air dispersion model was adopted from Arya et al. (1999), namely the Gaussian Plume Model (GPM), to assess the public risk. The effects of an accident involving airborne hazmats might be quantified as exposed population, the total number of people exposed to the possibility of an undesirable consequence due to the hazardous materials releases. For instance, the immediate dangerous life and health (IDLH) for propane exposure are 4,200,000 ppm for fatality and 600,000 ppm for injuries. At certain IDLH level, the operator identifies a safety distance threshold. Both terminals and routes consider the sources of hazmats releases. It was assumed a rectangular and circle dangerous zone for both edge and terminal source, respectively (given in Table 4.2 and illustrated in Figure 4.2). Technical details of the approximation function for the GPM and piecewise linearization for the transport risk can be found in Verma and Verter (2007) and Abuobidalla et al. (2019c), respectively.

Table 4.2: A summary of GPM for terminal and route.

Public Risks[a]	***Parameter***[b]	***Approximation function***
$PR_j^{node} = \pi\Phi_j(n_j)\hat{\rho}_j$	*Threshold area*	$\Phi_j(n_j) = \left[\sqrt[b_j+d_j]{\frac{n_j Q}{\pi\ u_j\ a_j\ c_j\ \bar{\mathcal{C}}}} \right]^2 : j \in d_l$
$PR_l^{edge} = 2\Theta_l(n_l)\rho_l q_l$	*Threshold distance*	$\Theta_l(n_l) = \left[\sqrt[b_l+d_l]{\frac{n_l Q}{\pi\ u_l\ a_l\ c_l\ \bar{\mathcal{C}}}} \right] : l \in L$

[a] $PR_j^{node}(PR_l^{edge})$: Population exposure at terminal j (along train leg l).
[b] The parameters is function of the hazmat volume being shipped (stored) along train service (terminal).
$a_l, b_l, c_l, d_l(a_j, b_j, c_j, d_j)$: Atmospheric parameters along train service l (terminal j)

Hazardous Materials Trip Plan Problem with Train Dispatching decisions

The considered routing and scheduling problem integrates train timetabling and rail freight transportation problem, respectively. The problem can be decomposed into train timetabling and rail freight transportation problem, respectively. The former problem can be defined as set of trains must be assigned to a set of possible timetables such as the track capacity constraints are satisfied and the overtaking between train services occurred at terminals. The latter problem determines the best itinerary for each demand to minimize the costs of serving the demands while satisfying the train capacities and risk thresholds constraints. The mathematical formulation of the HTPTD is given in Appendix C.

Hazardous Materials Trip Plan Problem with pricing decisions

Given the solution for HTPTD, we consider a railway company that operates $|L|$ direct train services within a railway network. Each direct train service $l \in L$, a train moves nonstop between two yards, starts at yard o_l, terminates at yard d_l and defined by a set of operational characteristics, i.e., the operation start time τ_l^o, cutoff time τ_l^c, schedule departure τ_l^d at origin yard, the schedule arrival τ_l^a at destination yard and the maximum number of cars U_l can be hauled by a train. In response to planned train services, the operator receives a sequence of future requests at the mids of the operation $k \in K_2$, referred to as *irregular requests*, in addition to the already existing scheduled requests $k \in K_1$ for carload moves, hereafter called request. At the arrival of irregular demand $k \in K_2$, the operator is given the pickup and delivery yard, the quantity of demand, the response time, the earliest pickup time and the latest delivery time of the demand. Then, the management decides the delivery and price quotations according to the current status of the railway network, service level required, type of demand, and available itineraries.

It was assumed that customers have full knowledge of the available train services provided by the carrier with regards to the services routes, en-route stops, and schedules. That is, all customers have full prediction information regarding the current and future network status and choose a service level that minimizes generalized cost function while meeting their needs. For example, some customers have more concerns about the transit time of their commodities than others and may pay premium service to deliver their demand. The revenue generated from serving a request is equal to the actual operating costs to ship demand: sorting, classification, shipping, and storing costs (if any), along the itinerary plus the profit margin for the carrier. The operator can either accept or reject the demand within a given amount of time called responding time T_k^{RES}, a similar strategy to the one studied in Yang et al. (2004); Zolfagharinia and Haughton (2014,1), among others. In the case demand $k \in K_2$ is accepted, it will be assigned to a sequence of train services by the operator.

As information of the railway requests is revealed, the operator might change the previous decisions to enhance the overall performance of the railway system. The operator may determine alternative itinerary of demand at any terminal along its route to release some spaces for a new request and/or to reduce the population exposure from hazamt transportation. Replanning of the already existing scheduled demands should be performed without breaking the delivery quotations. The selection of the alternative itineraries for the already scheduled demands involves several factors such as the time when the demand reveal, the position of the train services, the available capacity and remaining risk thresholds, and the itinerary compatibility among the itineraries. More specifically, the proposed heuristic algorithm allows insertion of both the current pending request and already existing scheduled requests in the way that the reinsertion of the already scheduled requests at some more globally beneficial. Of course, the new itinerary of demand is only constructed from its origin yard that the demand is currently holding or any terminal along the route without breaking the pricing and delivery quotations. One approach to accommodate future demands is to allocate dynamically the capacity on the train services as information of the new demands revealed similar to the one in Cao et al. (2012); Liu and Yang (2015) and may also reduce the population exposure associated with hazmat transportation (if any).

4.3.2 Formal notation for HTPP

To give full information of the railway status at any time t, we introduced sets and variables, including the position and location of the train services and schedule demands and the remaining capacities and risk thresholds for train services as follows:

(A) Train services: Initially, at time $t = 0$, all train services are idle at their origin's terminals. Each direct train service $l \in L$ will follow the train timetabling plan by solving HTPTD, assuming no deviation in the initial train plan. That is, train services arrive punctually following the initial timetables. Each train service l, $1 \leq l \leq L$, is at any time t, either idle, in-transit, in-motion or out of service. Let $S_l(t)$ be an integer with four possible

values: -1 (idle) if $0 \leq t < \tau_l^o$; 0 (in-transit) $\tau_l^o \leq t < \tau_l^c$; 1 (in-motion) $\tau_l^c \leq t < \tau_l^a$; and -2 (out of service) $\tau_l^a \leq t$. Let also $U_l(t)$ and $R_l(t)$ be the capacity and risk threshold of train service l at time t, respectively. We use continues variables to present the location of train at time t obtained from equation (39), where $L_l(t)$ denote the l's train's position at time t with four possible cases:

$$L_l(t) = \begin{cases} -\infty & t > \tau_l^a \\ o_l & 0 \leq t < \tau_l^d \\ o_l + \frac{t-\tau_l^d}{\tau_l^a-\tau_l^d}(d_l - o_l) & \tau_l^d \leq t < \tau_l^a \\ d_l & t = \tau_l^a \end{cases} \tag{39}$$

A railway operator may plot a string-line diagram, a time-location graph of where train services are and when (using equation 39). The vertical axis of the string-line diagram corresponds the terminals names and the horizontal axis represents time (illustrated in Figure 4.3 for a train starts at j_2 and ends at j_3 with two train legs). The train route and schedule are displayed diagonal, where the slope of the string-line determines the speed of the train. During its journey a train is stopped at a terminal, the string-line would be horizontal. A string-line graph depicts how train services are planned to operate in the future.

(B) Scheduled requests: We assumed that there are $|N(t)|$ known railway requests by time t, $N(t) = \{k : t > \tau_k^{AR}\}$. Out of the $N(t)$ request, a subset of $\phi(t)$ requests has to be served by the carrier own services. In case a request has been accepted become elements of the set $\phi(t)$. The other requests could be rejected if it is infeasible to fulfill the demands. Let $M(t)$ be subset of requests in $N(t)$ whose final acceptance or rejection decisions fixed at time t, $M(t) = \{k : t > \tau_k^{AR} + T_k^{RES}\}$. Under the proposed procedure, let $H_k(t)$ be either the itinerary which request k is currently followed, idle or the planned journey to be hauled. Let also $Q_k(t)$ be the position of request at time t under the last announced plan. Together with the fact that trains move at an average speed, it should be clear that $S_l(t)$, $L_l(t)$, $U_l(t)$,

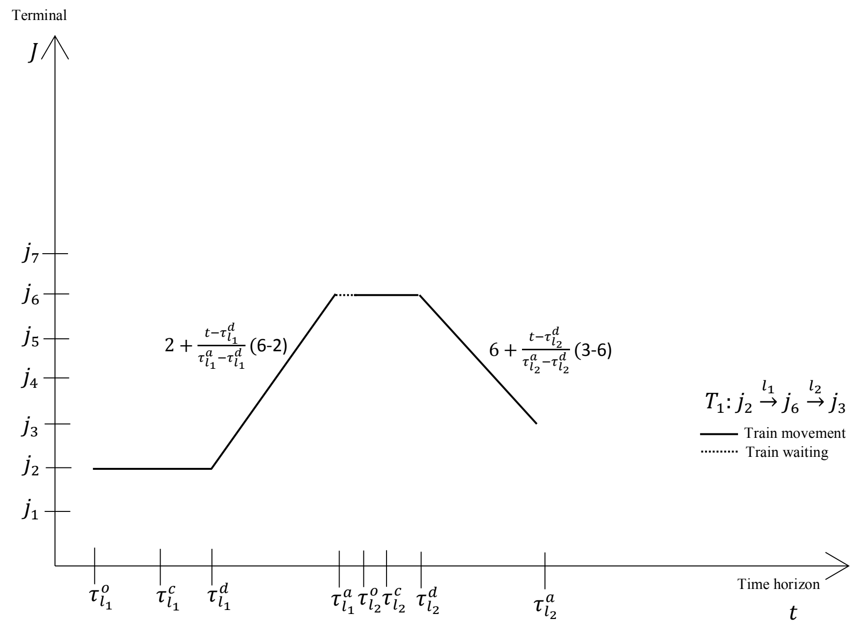


Figure 4.3: An example of string-line diagram.

$R_l(t)$, $1 \leq l \leq L$ and $H_k(t)$, $Q_k(t)$, $k \in N(t)$ give a full information of the railway status at time t.

At the arrival time of the irregular request τ_k^{AR}, $K_1 + 1 \leq k \leq K_2$, its characteristics are revealed through 5 parameters with the following definitions (some of those parameters are illustrated in Figure 4.4):

- o_k and d_k denote the pickup and delivery yard for demand k, respectively.

- D_k and H_k denote the quantity of regular and hazmat freights in request k, respectively.

- T_k^A defines the time between the arrival of request k and its earliest pickup time at o_k. The ready time is then obtained from the following expression: $\tau_k^{AL} = \tau_k^{AR} + T_k^A$, where τ_k^{AL} and τ_k^{AR} denote the available time and arrival time of request k, respectively.

- T_k^{SLK} denote the slack time between the earliest and latest allowed delivery time and reflect the tightness of demand's completion deadline. The operator can then estimate the final delivery time a demand can be delivered without penalty as follows: $\tau_k^{LD} = \tau_k^{AL} + \underline{t_k} + T_k^{SLK}$, where $\underline{t_k}$ is the minimum in-transit time for request k.

- Finally, T_k^{RES} is the time within which the operator must respond to the customer with final acceptance or rejection decision, usually specified through negotiation between the customer and carrier. Accordingly, the latest time for the railway operator to decide whether to accept or reject demand $k \in K_2$ is by $\tau_k^{AL} + T_k^{RES}$. Together with the current status of the railway network, the management decides the price to provide service:

  - b_k is the price in which the company charges the customer to provide train service or stated in contract and agreement between the customer and carrier. Accordingly, one may compute the shortest distance (minimum in-transit time) between the origin and destination of the demand, obtained from the set of admissible itineraries and the charge rate per commodity b_k, denoted as $\underline{d_k}$ ($\underline{t_k}$). Also, the operator may calculate the maximum distance (maximum in-transit time) demand can be travel without exceeding the actual cost from serving that request, concerning the price quoted and set of available train services, denoted as $\overline{d_k}$ ($\overline{t_k}$). The last feasible time, total costs equal revenue, to deliver the demand is derivable from the available itineraries for that request using the following equation: $\tau_k^{LF} = \tau_k^{AL} + \overline{t_k}$, where τ_k^{LF} is the latest time a request k can be delivered without exceeding the revenue generated from serving request k.

Before describing the proposed procedure, it is important to introduce the following the formulation for HTPP: given the information of trains with their position, train schedule, remaining capacity and risk threshold and already existing scheduled requests with their locations, obtain an optimal plan to serve these requests, assuming no future demands. The formulation is introduced as a problem being called repetitively at each request's arrival by the proposed procedure. The new dynamic model defines a sequence of temporary optimization problems being generated at the request's arrival. These problem instances are obtained from particular snapshots of the current executed trip plan. At any time

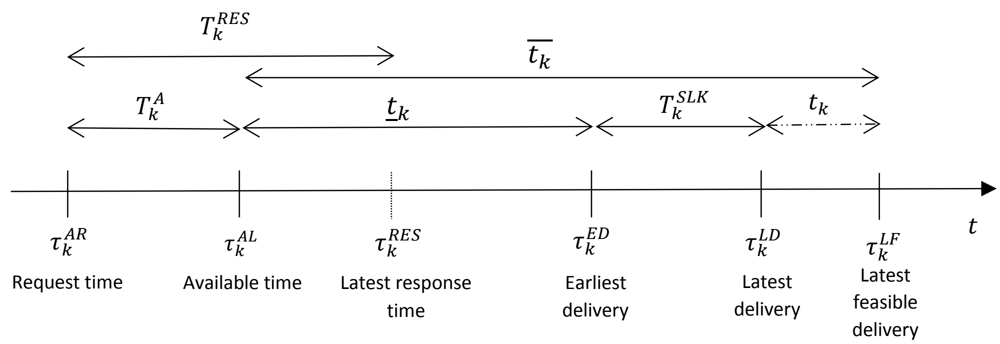


Figure 4.4: Request information.

that is not a request arrival, there is a previously published trip plan being executed and interrupted at each request's arrival τ^{AR}. Detail of the formulation for HTPP is given next.

The formulation for HTTP

Following Moccia et al. (2011), we outline the considered problem on a special graph. Let $G(V, A)$ be directed space-time multigraph in which a node represents either source, sink, or service. A source (sink) node represents the start (end) node for a request k, whereas service node describes a train service in set L. An arc in G represents either starting, ending, train connection or demand rejection edge. A definition of the graph components is illustrated in Figure 4.5. Arc set is partitioned into four sets:

- *Set of starting arcs* $(\sigma_k, L) \in A_1$ for each service in $L^{ACT}(t)$ and railway request in $N(t) \setminus M(t)$ including the current pending request k' given that the request is available at its origin not more than the cutoff time of that train service, $\tau_k^{AL} \leq \tau_l^c$ and $o_k = o_l$. The cost on those arcs represents the cost of shipping, inventory (if any), and classification,

- *Set of ending arcs* $(L, \eta_k) \in A_2$ for each service node in $L^{ACT}(t)$ and railway request in $N(t)\setminus M(t)$ including the current pending request k without exceeding the revenue generated for that request, $\tau_k^{LF} \leq \tau_l^a$ and $d_k = d_l$. The cost on those arcs represents the revenue generated plus penalty cost (if any),

- *Set of service connection arcs* $(l, l') \in A_3$ for each pair of service nodes in $L^{ACT}(t)$ that form a complete path from o_l to $d_{l'}$, $\tau_l^a \leq \tau_{l'}^c$, $d_l = o_{l'}$, and $l \neq l'$. The cost on the service connection represents shipping and train swap (if any) cost, and

- *Set of rejection arcs* $(\sigma_k, \eta_k) \in A_4$ for each railway request in $N(t) \backslash M(t)$.

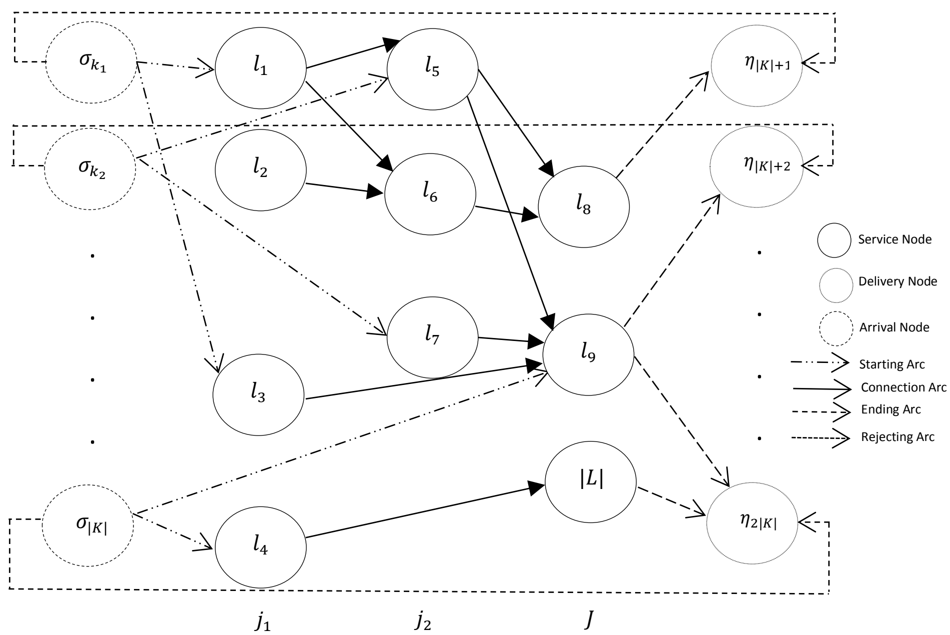


Figure 4.5: Space-time multigraph.

The offline problem is solved at each request arrival in the online strategy. Paths in G represent feasible itineraries for railway request k in $N(t)$ that starts at σ_k, transports along with one or several services in L and ends at η_k. A direct path from σ_k to η_k indicates that request k is rejected, i.e., served by a partner. At any time that is not a request arrival, there is a previously published plan being executed. At request arrival τ^{AR}, the published plans are interrupted and some new trip plans are generated for the shipments under consideration. We also require that the new trip plans decided by the procedure do not change the previous (fixed) decisions associated with requests by introducing set (σ_k, L).

Set (σ_k, L) in G is obtained from the last executed plan, where the location of a demand k either the current location of demand k if it is at origin terminal or the location at which demand k will finish its current train segment. That is, any decisions made at time τ^{AR} must only depend on the information known up to time t. To improve the readability of this chapter, sets, parameters and decision variables of the path-based formulation given Table 4.3-4.4.

Table 4.3: Sets, parameters, and decision variables (part 1 of 2).

Sets	
T	Planning horizon, index by $t \in T$.
K	Set of requests, index by k *or* $k' \in \{K_1 \cup K_2\}$.
K_1	Set of traditional requests, index by k *or* $k' \in K_1$.
K_2	Set of irregular requests, index by k *or* $k' \in K_2$.
J	Set of terminals in G, index by $j \in J$.
L	Set of train services, index by l or $i \in L$.
$L^{ACT}(t)$	Set of feasible train services at time t, index by l or $i \in L$, $L^{ACT}(t) = \{l \in L : t < \tau_l^c\}$.
$N(t)$	Set of railway requests revealed by time t, index by k, $N(t) = \{k \in K : t > \tau_k^{AR}\}$.
$M(t)$	Set of requests in $N(t)$ whose final acceptance or rejection decisions are fixed at time t, $M(t) = \{k \in N(t) : t > \tau_k^{AL} + \tau_k^{RES}\}$.
$I^{\Phi}(t)$	Set of railway requests under consideration at time t, index by k, $I^{\Phi}(t) = \{k \in N(t) \backslash M(t)\}$.
$\phi(t)$	Set of railway requests accepted at time t, index by k, $\phi(t) = \{k \in M(t) : H_k \neq \emptyset\}$.
V	Node set is partitioned into: *(a) Source nodes* σ for each request in $N(t)\backslash M(t)$ (index by σ_k), *(b) Service nodes* L for each service offered by the carrier (index by l), and (c) *Sink nodes* η for each request in $N(t)\backslash M(t)$ (index by η_k).
A	Arc set is partitioned into four sets: *(a) Set of starting arcs* $(\sigma_k, L) \in A_1$, *(b) Set of ending arcs* $(L, \eta_k) \in A_2$, *(c) Set of service connection arcs* $(L, L') \in A_3$, and *(d) Set of rejection arcs* $(\sigma_k, \eta_k) \in A_4$.
A_k	Subset of A such as commodity k can be shipped through, index by a.
$A_i^+(A_i^-)$	Set of emanating (ending) arc from node i, index by a.
I_k	Set of all feasible itineraries on G for request k, index by $v \in I_k$.
I	Set of all itineraries $I = \bigcup_k I_k$, index by v or $v' \in I$.
I_l	Subset of itinerary in I that use train service l.
I_j	Subset of itinerary in I that shipped through terminal j, $j \in J$.
Parameters	
o_a	Origin node of arc a, $o_a \in J$.
d_a	Destination of arc a, $d_a \in J$.
o_k	Origin yard of request k, $o_k \in J$.
d_k	Destination yard of request k, $d_k \in J$.
o_l	Origin yard of train service l, $o_l \in J$.
d_l	Destination yard of train service l, $d_l \in J$.
$\gamma_{v,l}$	Indicator =1 if itinerary v uses train service l; 0 otherwise.
τ_l^o	Schedule operation start time of the train service l at yard $o_l \in J$.
τ_l^c	Schedule cutoff time of the train service l at yard $o_l \in J$.
τ_l^d	Schedule departure time of the train service l at yard $o_l \in J$.
τ_l^a	Schedule arrival time of the train service l at yard $d_l \in J$.
$c_{k,v}$	Per unit net profit to transport request k along itinerary $v : v \in I_v$.
$\Omega_{v,v',j}$	Indicator =1 if it is feasible to reschedule demand's itinerary from v to v' at terminal j considering the time along the route; 0 otherwise.

Table 4.4: Sets, parameters, and decision variables (part 2 of 2).

$\Delta c_{v,v',j}$	Per unit difference in the net profit if a demand reschedule from itinerary v to v' at terminal j, $\Delta c_{v,v',j} = c_{k,v'} - c_{k,v}$.
$\gamma^{A}_{v,v',j,l}$	Indicator =1 if the load on train service l increases when a demand rescheduled from itinerary v to v' at terminal j; 0 otherwise.
$\gamma^{R}_{v,v',j,l}$	Indicator =1 if the load on train service l decreases when a demand rescheduled from itinerary v to v' at terminal j; 0 otherwise.
ρ_l	Average population concentration along the train service $l : l \in L$.
q_l	Distance of the train service $l : l \in L$.
$\widehat{\rho_j}$	Average population concentration at yard j, $j \in J$.
$U_l(t)$	Remaining number of railcars can be hauled by a train service l at time t (Residual capacity).
$n_l(n_j)$	Number of dangerous goods (auxiliary variable) along train service l (through terminal j).
D_k	Number of regular railcars in request k to be shipped, $k \in K$.
H_k	Number of hazmat railcars in request k to be shipped, $k \in K$.
$\Theta_l(n_l)$	Threshold distance (auxiliary variable) to ship n_l hazmat freights along train service l, $l \in L$.
$\Phi_j(n_j)$	Threshold area (auxiliary variable) to ship n_j hazmat freight through terminal j, $j \in J$.
$R_l(t)$	Remaining population exposure threshold along train service l at time t.
$L_l(t)$	l's train's position at time t.
$H_k(t)$	Sequence of train services (if any) followed by a request k at time t.
$Q_k(t)$	Location of request k is either currently holding or the en-route stop heading to given by the last published plan.
Variables	
b_k	Per unit price to serve request k by the carrier's own services.
$x_{k,v,v',j}$	=1 if request k changes its latest published itinerary v to v' at terminal j; 0 otherwise.
$z_{k,v}$	=1 if current pending request k shipped through itinerary v; 0 otherwise.
$n_{l,j}$	Change in number of hazmat shipped along with train service l passing through yard j.
n'_l	Change in number of freight shipped along with train service l.

We developed two equivalent formulations of the considered problem. The first formulation is a multi-commodity network flow type with the flow on arcs, and the second model is a path-base formulation with the flow on paths. Empirically, the first formulation is not as competitive as the second one, thus we omit its details here. At request's arrival ($t = \tau^{AR}$), the path formulation for the HTPP is given below:

$$(P_8) \quad Max\ Z = \overbrace{\sum_{\substack{k':\\ t=\tau^{AR}_{k'}}} \sum_{v \in I_{k'}} c_{k',v} D_k z_{k',v}}^{\text{Net profit (pending request)}} + \overbrace{\sum_{k \in I^{\Phi}(t)} \sum_{\substack{v:\\ v=H_k(t)}} \sum_{v' \in I_k} \sum_{\substack{j:\\ \Omega_{v,v',j}=1}} \Delta c_{v,v',j} D_k x_{k,v,v',j}}^{\text{Change in net profit (already scheduled requests)}}$$

$s.t.$

$$\sum_{v \in I_{k'}} z_{k',v} \leq 1 \qquad k' : t = \tau^{AR}_{k'} \tag{40}$$

$$\sum_{\substack{v:\\ v=H_k(t)}} \sum_{v' \in I_k} \sum_{\substack{j:\\ \Omega_{v,v',j}=1}} x_{k,v,v',j} \leq 1 \qquad k : k \in I^{\Phi}(t) \tag{41}$$

$$n'_l \leq U_l(t) \qquad \forall l : l \in L^{ACT}(t) \tag{42}$$

$$2\Theta_l(n_{l,j})\rho_l q_l + \pi \Phi_j(n_{l,j})\hat{\rho}_j \leq R_l(t) \qquad \forall l, j : j \in d_l \tag{43}$$

$$n'_l = \sum_{\substack{k':\\ t=\tau^{AR}_{k'}}} \sum_{v \in I_{k'} \cap I_l} D_k z_{k',v} + \sum_{k \in I(t)} \sum_{\substack{v:\\ v=H_k(t)}} \sum_{v' \in I_k} \sum_{j \in J} (\gamma^A_{v,v',j,l} - \gamma^R_{v,v',j,l}) D_k x_{k,v,v',j} \forall l \tag{44}$$

$$n_{l,j} = \sum_{\substack{k':\\ t=\tau^{AR}_{k'}}} \sum_{v \in I_{k'} \cap I_l} H_k z_{k',v} + \sum_{k \in I(t)} \sum_{\substack{v:\\ v=H_k(t)}} \sum_{v' \in I_k} \sum_{j \in J} (\gamma^A_{v,v',j,l} - \gamma^R_{v,v',j,l}) H_k x_{k,v,v',j} \forall l, j \tag{45}$$

$$z_{k',v} \in \{0,1\} \qquad \forall k', v : \tau^{AR}_{k'} = t, v \in I_{k'} \tag{46}$$

$$x_{k,v,v',j} \in \{0,1\} \qquad \forall k, v, v', j : k \in I^{\Phi}(t), v, v' \in I_k, \Omega_{v,v',j} = 1 \tag{47}$$

$$n'_{l,j} \geq 0; n_{l,j} \geq 0 \ and\ R_+ \qquad \forall l, j : j \in d_l \tag{48}$$

Objective function Z in the above presented model (P_8) is to maximize the net profit from serving the railway requests. That is, total revenues from serving commodities minus the total costs including the cost of waiting for classification and connections, and the cost of using partner services (if any). Note that if a railway request served by a partner then the net profit of that request is zero by setting the cost on the set of rejection arcs to the partner cost. This cost reflects the gross revenue in which railway carrier would have otherwise obtained had it accepted the request. The first term in Z is the net profit from serving the current pending request, whereas the second term calculates the changes in the net profit from rescheduling the already existing scheduled requests. Constraints (40) and (41) are commodity flow conservation constraints for the current pending request and already existing scheduled requests. Constraints (42) are train capacity constraints for the planned services. Constraints (43) ensure that the total population exposure is not greater than the given thresholds, the first term in Constraints (43) is the sum of population exposure along the routes and the second term is that at yards. This risk thresholds could be mandated by a regulatory body external to the railway company or could correspond to a decision made internally by management to adhere to specific limits on population exposure. The risk thresholds constraints are to avoid over usage of certain train services. The total change in quantity of freights shipped along with train service l is defined by Constraints (44), whereas the change in the total change in quantity of hazmat freights shipped along with train service l is expressed by Constraints (45). Constraints (46)-(48) are binary and integer variable requirements.

The considered problem is a version of the Multicommodity Minimum Cost Network Flow Problem (MCNFP) with nonlinear constraints to account the risks associated with hazmat transportations. Although the special versions of the MCNFP can be efficiently solved in polynomial time, some generalizations of the MCNFP are intractable. An integer flow for the minimum cost multicommodity flow such as when routing nonbifurcated units of traffic is computationally expensive. Even et al. (1976a) proved that the unsplittable version of MCNFP to be NP-complete. Furthermore, the flow over time MCNFP is known to be NP-hard (Cai et al., 2001). The complexity of the considered problem causes a heavy computational burden from its solution. In this research, two-phase heuristic procedure is proposed to solve the considered problem. In the first phase, the algorithm is solve freight transportation and train scheduling problem for demands known in advance. In the second phase, an optimization model is build and solved at request arrival. Technical details of the solution method will be presented next.

4.4 Solution method

A two-phase heuristic solution method is proposed. In the first phase, we solve the HTTDP by a heuristic method. The solution of the HTTDP determines the schedule of the train services and the best demand-itinerary assignment decisions for the traditional demands. A preprocessing procedure is then applied to generate all compatible itineraries for the already existing scheduled demands (in Subsection 4.4.1). In the second phase, a sequence of subproblems are solved at arrival time of request τ^{AR}. The phase consists of two main steps. The pricing decision is determined first, considering the status of railway with and without the pending request. An optimization-based model is then built and solved considering the position of train services and already existing scheduled demands (in Subsection 4.4.2). The overall goal of this procedure is to generate itineraries or (sub)itineraries for the already existing scheduled demands. More specifically, the proposed heuristic algorithm allows insertion of both the current pending request and already existing scheduled requests in the way that the reinsertion of the existing scheduled demands at some more globally beneficial by solving the linear version of P_9. Technical details of the preprocessing procedure and the second phase is discussed and followed by a summary of the whole solution method in Subsection 4.4.3.

4.4.1 Pre-processing procedure

The aim of these subroutines is to generate all alternative itineraries of the demand and reformulate the model in order to be fed and solved using a MIP solver more efficiently. The following alternative (sub)itinerary enumeration and route generation procedure is applied once in the heuristic, given the information of a rail network and the timetables of train services.

Alternative itinerary generation process

Relying on exhaustive alternative (sub)itinerary enumeration and route generation heuristic for the already existing scheduled requests are often computationally expensive (Szeto et al., 2017). To work around that, we design a preprocessing procedure to enumerate all alternative plans for each available itinerary. This is achieved by constructing one or more alternative itineraries for demands. The alternative itinerary generation process is applied to one itinerary at a time without taking into account capacity constraints but only considering feasibility in terms of time delivery and train connection. The procedure is attractive for medium or large networks to avoid exhaustive and time consuming to generate a complete alternative itinerary set when a new shipment arrives.

Function linearization

To simplify computation, in the second part of the preprocessing, piecewise linear functions were used to substitute the nonlinear hazmat risk functions in GPM model (in Constraints (43)). The resulting optimization model can be solved using popular MIP commercial software, without invoking the search for local or global optimal solutions of a nonlinear problem. For expositional reasons and for sake of brevity, we do not repeat the methodology details, and we invite the reader to refer to Abuobidalla et al. (2019c).

4.4.2 Pricing problem and HTTP

In deciding the price of pending request, we adopt a simple pricing strategy called Cost-Plus Profit similar to the one discussed in Li et al. (2015) with some modifications to the considered problem. The pricing of train services is often setup based on a Cost-Plus basis, in which the operator calculates the actual costs incurred from serving the demand and then applies a markup percentage to the costs (Calvo and De Oña, 2012; Jarocka, 2016; Littlechild, 1970). The markup is stipulated by the customer, as often the case with government contracts, or it can be estimated by the carrier. Before we introduce the pricing strategies, some important assumptions are made and listed below:

- For railway freight transport service offered by the operator, there is always a market price and often this price known to both operator and customers. The operator price quotations are not more expensive than the corresponding market price.

- The railway freight transport operator has different target profit margin for different types of train services.
- The railway freight transport service price is determined and quoted when the operator responses to their customer with final offer and will not change even if the actual execution of the delivery deviates later.

In all the proposed pricing strategies, we evaluate each request with respect to two conditions, called *feasibility* and *profitability*. For the feasibility criteria, we make sure that at least one itinerary is available to serve the new request at the time of arrival, whereas the other condition guarantees that at least one of the available itineraries is profitable. If the two conditions are satisfied, then the operator prepares the price and delivery quotations of that pending request. Otherwise, the operator may refuse the demand by offering a price more than the market price.

In the first pricing policy, called *base pricing*, the operator determines the best and final price regardless of the status of the railway network. The price is equivalent to the actual costs for serving the request plus profit margin of the carrier. The actual cost of particular freight is estimated by identifying the amount of various intermediate activities needed to transport the demand from its origin to destination, i.e., shipping, resorting, holding and etc. In the other pricing strategies, the operator collects some performance indicators (I) before deciding the price of the pending request. The basic idea of those pricing strategies is to evaluate the current performance of railway with and without the current pending request. The operator then decides the charge to provide such service to compensate the additional loads on train services and increases in population exposure associated with hazardous materials transportation (if any). A simple pricing scheme is given below (illustrated in Figure 4.6):

$$
b_k = \begin{cases} \bar{b}_{o_k,d_k} & a \le I < b \\ f_1 \bar{b}_{o_k,d_k} & b \le I < c \\ f_2 \bar{b}_{o_k,d_k} & c \le I \le d \end{cases}
$$

where $\bar{b}_{o_k,d_k}$ denotes base price for a commodity originates at o_k and must be delivered to d_k, and a, b, c, d, f_1, f_2 are pricing parameters ($a < b < c < d$ and $f_2 > f_1$) that can be calibrated by the operator. I is a parameter to measure the impact from serving the current pending request with respect to additional train load and risk (if any). The propose pricing mechanism is simple: the sooner the customer make the order, the lower the price.

Table 4.5: Characteristics of pricing strategies.

Charac./strategy	*Fixed/Dynamic*	*Criteria*	I_1	I_2
*base pricing**	*Fixed*	–	–	–
OD pricing	Dynamic	itineraries for OD	$\sum_{v \in I_k} \Big(\sum_{l \in L_v} \Big(\sum_{\substack{k' \in N(t): \gamma_{v',l}=1 \\ v'=H_{k'}(t)}} D_{k'}/U_l^{INI} \Big) \Big) \Big/ \bar{n}_v \lvert I_v \rvert$	$\sum_{v \in I_k} \Big(\sum_{l \in L_v} \Big(\delta_l \Big) \Big) \Big/ \bar{n}_v \lvert I_v \rvert$
path pricing	Dynamic	itineraries for all ODs	$\sum_{v \in I} \Big(\sum_{l \in L_v} \Big(\sum_{\substack{k' \in N(t): \gamma_{v',l}=1 \\ v'=H_{k'}(t)}} D_{k'}/U_l^{INI} \Big) \Big) \Big/ \bar{n}_v \lvert I_v \rvert$	$\sum_{v \in I} \Big(\sum_{l \in L_v} \Big(\delta_l \Big) \Big/ \bar{n}_v \lvert I_v \rvert$
train pricing	Dynamic	remaining capacities	$\sum_{l \in L} \sum_{\substack{k' \in N(t): \gamma_{v',l}=1 \\ v'=H_{k'}(t)}} D_{k'}/U_l^{INI} \lvert L \rvert$	$\sum_{l \in L} \delta_l / \lvert L \rvert$

*The base pricing for an OD shipment obtained from: $\bar{b}_{o_k,d_k} = \sum_{v \in I_k} c_{k,v} / \lvert I_v \rvert$

**$\delta_l = [2\Theta_l(n_{l,j})\rho_l q_l + \pi \Phi_j(n_{l,j})\hat{\rho}_j] / R_l(t)$

**Performance indicator $I = [\alpha \Delta I_1 + (1-\alpha)\Delta I_2]/2$, where $\alpha \in \{0, 1\}$ indicates the importance of train capacity compare to risk threshold ΔI_1, ΔI_2 are the average change in train capacity and population exposure indicator when request k' is served.

The *OD and path* pricing strategies use both the average utilization of the train sequences and the ratio of the total population exposure to the given risk threshold to determine the price of pending request. The difference between OD and path pricing strategies is that the former focuses on train sequences for an OD rather than all OD shipments. The last pricing strategy, called *train pricing*, determines the price quotation based on the average train utilization and average ratio of population exposure to the risk threshold. In all the proposed pricing strategies, we differentiate the hazmat and regular freights by charging the hazmat freight additional fees for extra safety requirements. A summary of the four pricing policies proposed is given in Table 4.5.

Giving the pricing decision, an optimization-based model is built and solved considering

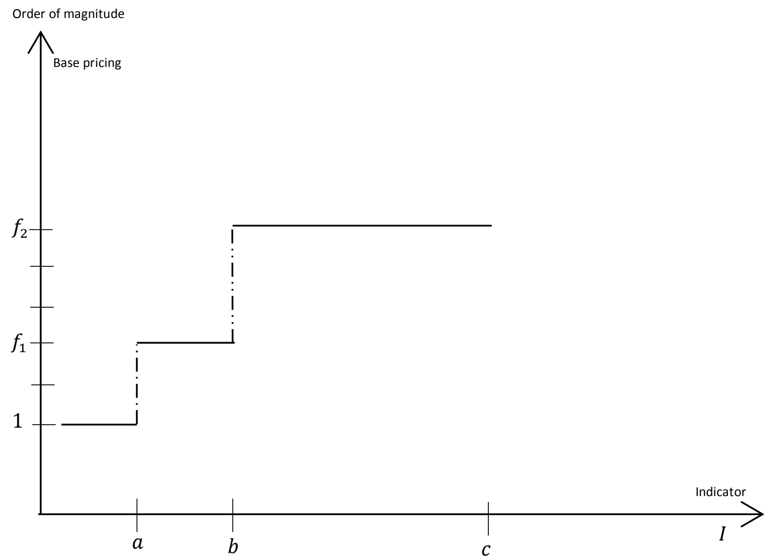


Figure 4.6: Cost Plus Profit.

the position of train services and already existing scheduled demands. The overall goal of this procedure is to generate an itinerary or (sub)itinerary for the already existing scheduled demands and pending request while minimizing the additional costs to accommodate the current pending request as if no future new request would ever be revealed.

4.4.3 A summary of the solution procedure

The main steps of the heuristic is given in Algorithm 3 (depicted in Figure D.1).

Algorithm 3 Main steps of the heuristic.

Phase 1: Solving the HTPTD and pre-processing subroutines:
Step 1.1 Read data: network information, traditional requests, list of candidate train services, risk parameters.
Step 1.2 Solve hazardous materials trip plan problem with train scheduling decisions by a heuristic method (Appendix C).
Initial trip plan (traditional requests) and timetables of train services.
Step 1.3 Pre-processing subroutines (Subsection 4.4.1):
Find initial train capacity ($U_l(0)$) and initial risk threshold ($R_l(0)$).
Determine all alternative itineraries: $\gamma_{v,l}$,$\Omega_{v,v',j}$,$\Delta c_{v,v',j}$,$\gamma^A_{v,v',j,l}$,$\gamma^R_{v,v',j,l}$.
Function linearization for Constraints (43).
Phase 2: Solving the HTTP:
Step 2.1 If t is request arrival $t = \tau^{AR}$:
Record information of the request: Demand volume, pickup and delivery yard, earliest pickup time, slack time and response time.
Compute base pricing $\bar{b}_{o_k,d_k}$, change in train capacity ΔI_1 and population exposure ΔI_2.
Determine price to fulfill the demand: base pricing, OD pricing, path pricing, train pricing (Subsection 4.4.2).
Populate and solve the linear version of P_4 to optimality.
Update the trip plans, train capacities, and risk thresholds.
Step 2.2 If t is not request arrival $t \neq \tau^{AR}$:
Update current location of train services $L_l(t)$ and position for already existing scheduled demand under investigation $Q_k(t)$.
Update set of feasible train services $L^{ACT}(t)$, remaining capacity $U_l(t)$, risk threshold $R_l(t)$ and set of request under investigation $I^{\Phi}(t)$ Go to 2.1 if $t = \tau^{AR}$ or Go to 2.2 if $t \neq \tau^{AR}$.
Export the best train timetabling and rail freight transportation decisions

4.5 Computational results

4.5.1 Computational setting

The algorithm procedure was implemented in *C*++, in particular, the MIP linear optimization was solved using Cplex *v*.12.7.1 and the ILOC Concert technology for building the model from the *C*++ language. The purpose of our computational experiments is to compare the proposed pricing strategies under the same parameters. Throughout our experiments, we assume that (1) request arrival rate λ to be $1/T^{INT}$, where T^{INT} is average of request interarrival in unit time; (2) origin and destination yards of the requests and demand rate are independently identified; and (3) T_k^A, T_k^{SLK} and T_k^{RES} are all generated independently from uniform distribution with mean $T_{i,j}^A$, $T_{i,j}^{SLK}$, $T_{i,j}^{RES}$, and ranges $[0, 2T_{i,j}^A]$, $[0, 2T_{i,j}^{SLK}]$, and $[0, 2T_{i,j}^{RES}]$: $i = o_k$ and $i = d_k$. Moreover, the cost term was adopted from Fang et al. (2017); Verma et al. (2011). In particular, the transportation cost for regular and hazmat freight was assumed to be \$0.875 and \$1.630 per mile, respectively. The classification cost per regular freight was assumed to be \$150, whereas hazmat freight was estimated to be a 20% additional charge than the cost of regular freight, i.e., insurance, security and safety costs. The inventory cost per freight was assumed to be \$50 per day.

4.5.2 Hypothetical network

The proposed solution method is applied to a hypothetical railway network, given in Figure 4.7, to evaluate various pricing strategies in the presence of hazmat freights. The network consists of 11 terminals and 21 links. We designed 12 train journeys given in Table 4.6. Each train service consists of one to four train legs with different atmospheric class, i.e. A-F. A total of 32 train legs has been created to satisfy any request in K and resulting in a total of 232 possible itineraries. The study uses two sets of freight flow data, one for the known requests in advance, whereas the other for the additional requests revealed during the planning horizon. Table 4.7 gives the schedule and utilization with respect to the initial plan produced by solving HTPTD.

At the beginning of planning $t = 0$, there were 131 customer requests routed and scheduled to be shipped along with specific train sequences by a heuristic method solution. A total net profit of \$108615 was obtained from the traditional requests (518 regular and 265 hazmat freights), with a total of 1.8 million people exposed to risk. The 131 requests utilized almost 43% of the capacity of planned train services and about 40% of the capacity of the available train sequences. The remaining capacities are available to accommodate some future demands. The proposed procedure is then applied using the base pricing strategy. On average of 90 extra requests, 589 carloads with 182 hazard shipments, have been accepted and scheduled into the current planned train services and increased the total net profit to

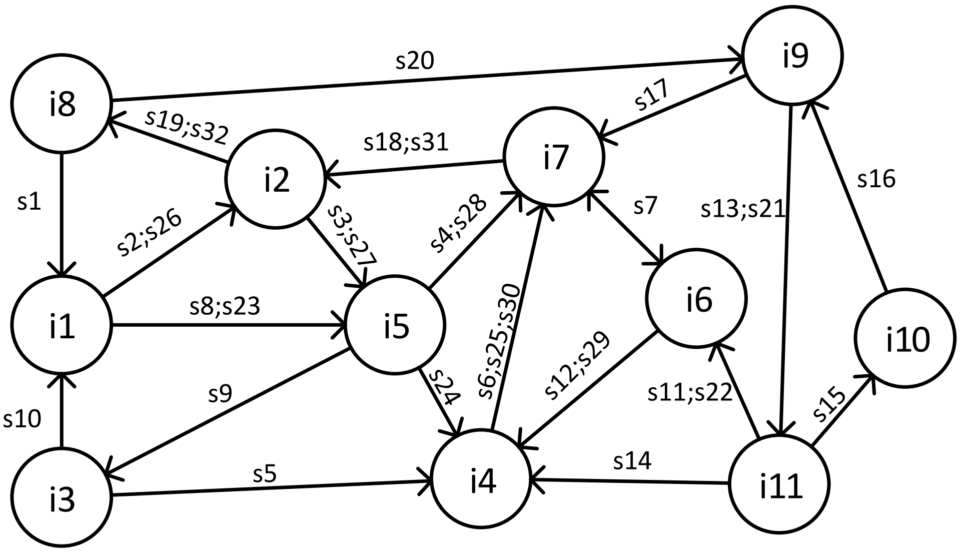


Figure 4.7: Hypothetical railway network.

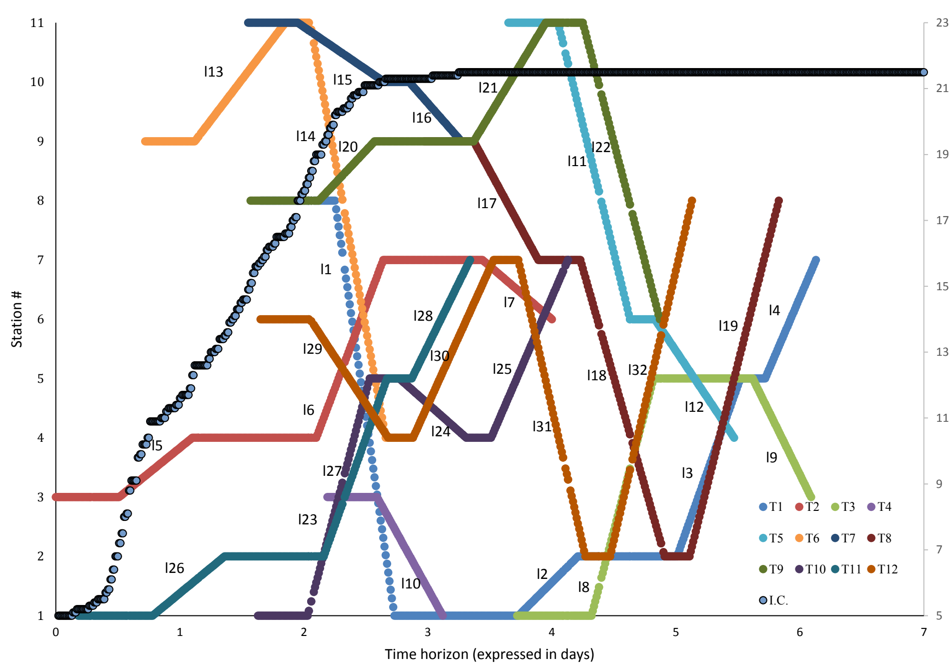


Figure 4.8: Timetable vs. total number of revised itineraries.

\$208377. The extra 182 hazardous materials increases the total population exposure to 2.9 million people (on an average increase of 61.11%), for the additional dangerous goods.

Together with Table 4.7, Figure 4.8 depicts how train services are planned to operate in the future and the total number of requests that will be rescheduled as a function of time. The x-axis in Figure 4.8 gives the time expressed in days where the first y-axis (left) is the terminal number and the second y-axis (right) is the total number of requests rescheduled. It is clear from Figure 4.8 that the number of requests that deviated from their last published plan decreases as a function of time. The decrease in the flexibility results from the fact that many requests reach their corresponding response times, in which the operator must fix their itineraries and the price and delivery quotations. Also, there are few routing and scheduling alternatives exists as some train services reach their corresponding cutoff times. This reveals that the railway operators should adapt their pricing strategy at least to compensate for the additional loads on train services and increases in transport risk (if any). From an operator's perspective, request contract often considered independently and a pricing decision needs to made for each request.

We report the net profit values as a function of time rather than one value for all the requests at end of the planning horizon. To show the impact of accepting additional requests after the traditional requests are scheduled, we draw the number of itineraries that deviated from the last published train sequence and net profit over the planning horizon, given in Figure 4.9. As the operator accepts more commodities, the total net profit increase through the planning horizon. However, the rate of increase in net profit varies from one period to another. One may divide the planning horizon into three ranges (or more), very dramatic increases from $t = 0$ to $t = 1.4$, gradual between $t = 1.4$ to $t = 5.2$, and very little after $t = 5.2$. In the first period, the increase in the net profit is almost linear as a function of time compared to the other ranges, i.e., from $t = 0$ to $t = 1.4$ at a rate of \$2046 per hour (\$49119 per day/24 hour per day). At the first period, adding the demand to the current train services is feasible and profitable as only additional fuel and equipment are needed. In other cases, the existing itineraries may need to be revised causing the increased cost of transporting the already existing scheduled freights and significant increases in population exposure.

Table 4.6: Information of the train services.

$\mathcal{T}$	*Journey*
t_1	$i_8 \xrightarrow{l_1} i_1 \xrightarrow{l_2} i_2 \xrightarrow{l_3} i_5 \xrightarrow{l_4} i_7$
t_2	$i_3 \xrightarrow{l_5} i_4 \xrightarrow{l_6} i_7 \xrightarrow{l_7} i_6$
t_3	$i_1 \xrightarrow{l_8} i_5 \xrightarrow{l_9} i_3$
t_4	$i_3 \xrightarrow{l_{10}} i_1$
t_5	$i_{11} \xrightarrow{l_{11}} i_6 \xrightarrow{l_{12}} i_4$
t_6	$i_9 \xrightarrow{l_{13}} i_{11} \xrightarrow{l_{14}} i_4$
t_7	$i_{11} \xrightarrow{l_{15}} i_{10} \xrightarrow{l_{16}} i_9$
t_8	$i_9 \xrightarrow{l_{17}} i_7 \xrightarrow{l_{18}} i_2 \xrightarrow{l_{19}} i_8$
t_9	$i_8 \xrightarrow{l_{20}} i_9 \xrightarrow{l_{21}} i_{11} \xrightarrow{l_{22}} i_6$
t_{10}	$i_1 \xrightarrow{l_{23}} i_5 \xrightarrow{l_{24}} i_4 \xrightarrow{l_{25}} i_7$
t_{11}	$i_1 \xrightarrow{l_{26}} i_2 \xrightarrow{l_{27}} i_5 \xrightarrow{l_{28}} i_7$
t_{12}	$i_6 \xrightarrow{l_{29}} i_4 \xrightarrow{l_{30}} i_7 \xrightarrow{l_{31}} i_2 \xrightarrow{l_{32}} i_8$

The variation in profit increase may happen for two reasons. First, the number of requests that can be rescheduled at the beginning of planning as information of the irregular demands are revealed is more than the case when requests show up at the end of the planning period, i.e., $t > 2.5$. For instance, the number of commodities revised from the last recent itinerary declined from 9.93 changes per day at the first range to 2.08 changes per day at the second range. Similarly, the total number of (hazmat) freights accepted decreases at the end of the planning horizon, see Figure 4.12 (Figure 4.13). The second reason is that the number of routing and scheduling options decreases as a function of time. Train services reaches their corresponding cutoff times as time moves. Figure 4.11 depicts the number of train services that reached their cutoff times (left y-axis) and the total number of available train sequences (right y-axis) as a function of time. A total of 242 train sequences are available to be assigned to the incoming requests at the beginning of the planning horizon. As time moves, the total number of train sequences declined. For example, 11 train service reach their cutoff times by $t = 2.06$ and thus the number of train sequences declined from 232 to 100 (over 56%). As a result of decreasing the number of available train sequences, the requests reveal after the first quarter of the planning will most likely follow longer paths,

Table 4.7: Timetable of the available train service.

L	τ_l^o	τ_l^c	τ_l^d	τ_l^a	U_1^*	U_2^{**}	L	τ_l^o	τ_l^c	τ_l^d	τ_l^a	U_1^*	U_2^{**}
l_1	1.65	1.95	2.25	2.73	20.93	3.45	l_{15}	1.55	1.85	1.95	2.65	23.19	3.45
l_2	3.13	3.43	3.73	4.21	72.22	6.47	l_{16}	2.54	2.75	2.85	3.27	59.59	6.90
l_3	4.61	4.91	5.01	5.52	62.39	25.43	l_{17}	2.97	3.27	3.37	3.89	61.54	8.19
l_4	5.42	5.62	5.72	6.13	15.94	5.17	l_{18}	3.83	4.13	4.23	4.91	70.59	31.03
l_5	0.00	0.25	0.51	1.10	4.32	9.48	l_{19}	4.80	5.01	5.11	5.83	66.94	14.66
l_6	1.50	1.80	2.10	2.64	9.93	8.62	l_{20}	1.57	1.87	2.12	2.57	27.19	3.88
l_7	3.04	3.34	3.44	4.00	22.97	5.17	l_{21}	2.97	3.27	3.37	3.95	70.71	5.17
l_8	3.72	4.01	4.32	4.82	61.17	3.45	l_{22}	3.85	4.05	4.25	4.87	60.33	2.16
l_9	5.22	5.52	5.62	6.09	62.18	12.93	l_{23}	1.63	1.93	2.02	2.52	36.84	6.47
l_{10}	2.19	2.49	2.59	3.12	38.68	3.45	l_{24}	2.43	2.67	2.77	3.31	22.95	5.17
l_{11}	3.65	3.95	4.05	4.63	44.44	4.31	l_{25}	3.21	3.41	3.51	4.13	61.32	13.79
l_{12}	4.53	4.73	4.83	5.47	68.38	4.74	l_{26}	0.18	0.48	0.78	1.36	0.00	6.03
l_{13}	0.72	1.02	1.12	1.85	7.03	9.05	l_{27}	1.76	2.06	2.16	2.67	24.77	6.90
l_{14}	1.75	1.95	2.04	2.66	43.09	13.79	l_{28}	2.57	2.77	2.87	3.34	67.21	6.03
l_{29}	1.65	1.95	2.04	2.68	19.69	6.90	l_{30}	2.58	2.78	2.88	3.53	36.60	20.69
l_{31}	3.43	3.63	3.73	4.26	64.71	18.97	l_{32}	4.17	4.37	4.47	5.13	64.91	6.03

*Utilization of train service ($U_1 = \sum_{k \in K_1} \sum_{v \in I_k \cap I_l} D_k x_{k,v} / U_l$);

**Utilization of train sequence ($U_2 = \sum_{v \in I_l} \sum_{k \in K_1} \sum_{v' \in I_k \cap I_l} D_k x_{k,v'} / U_l$);

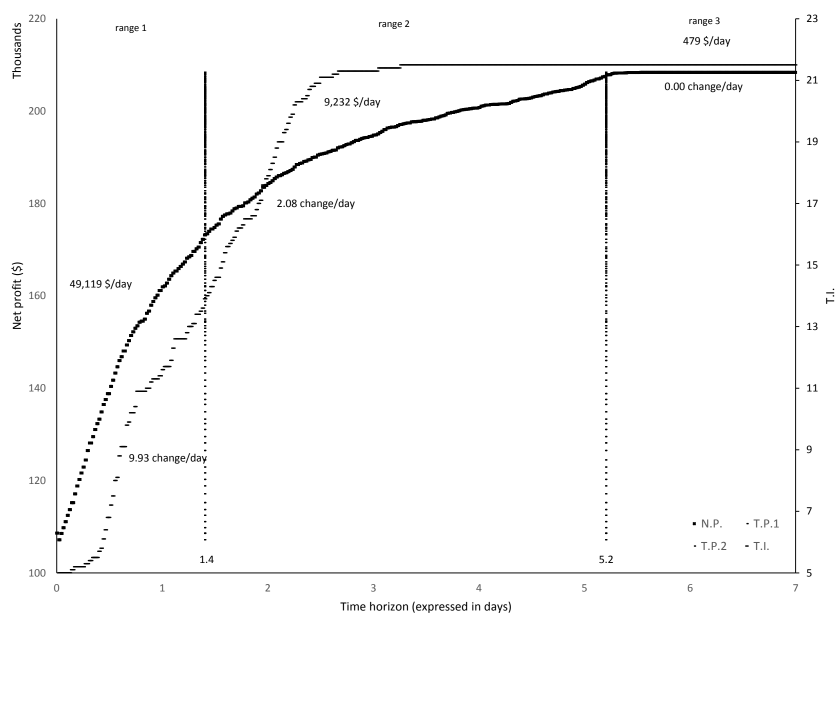


Figure 4.9: Net profit vs. # itineraries deviate.

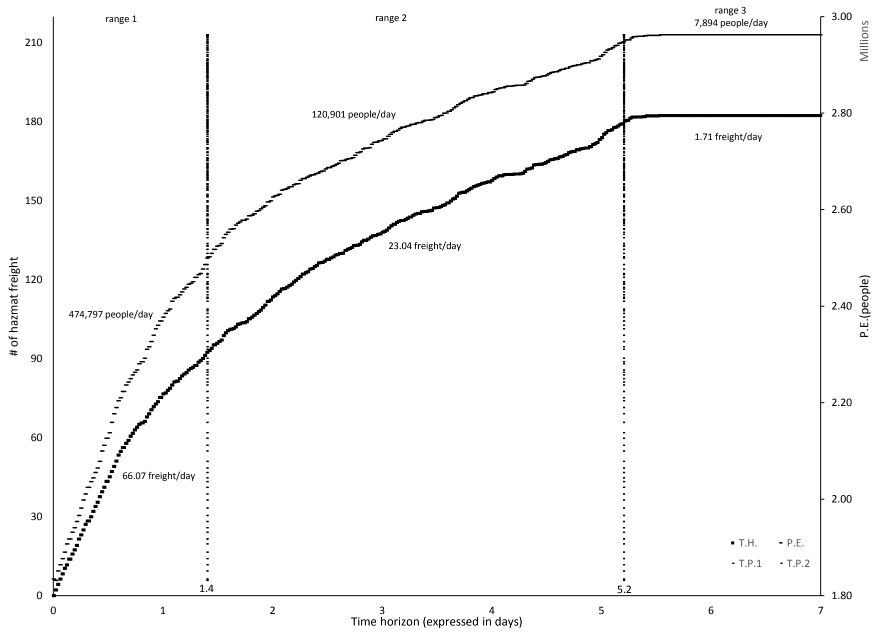


Figure 4.10: Net profit vs. population exposure.

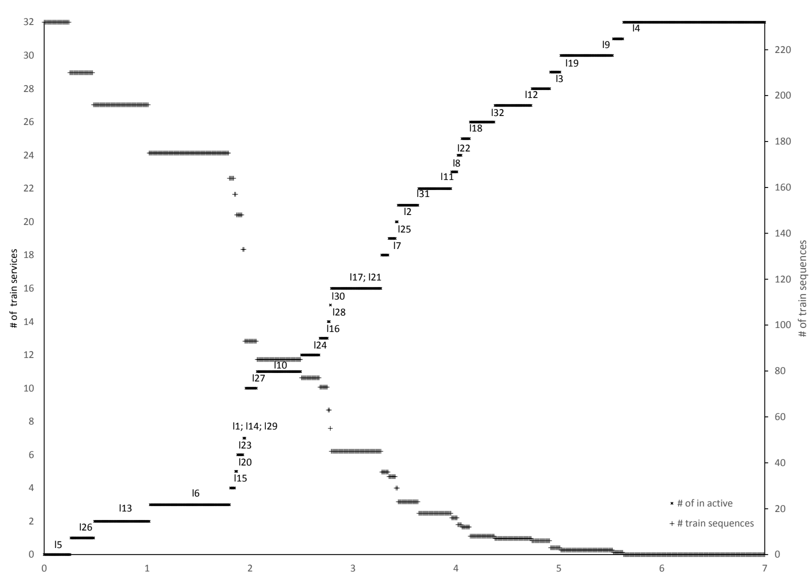


Figure 4.11: # of train services vs. # of train sequences

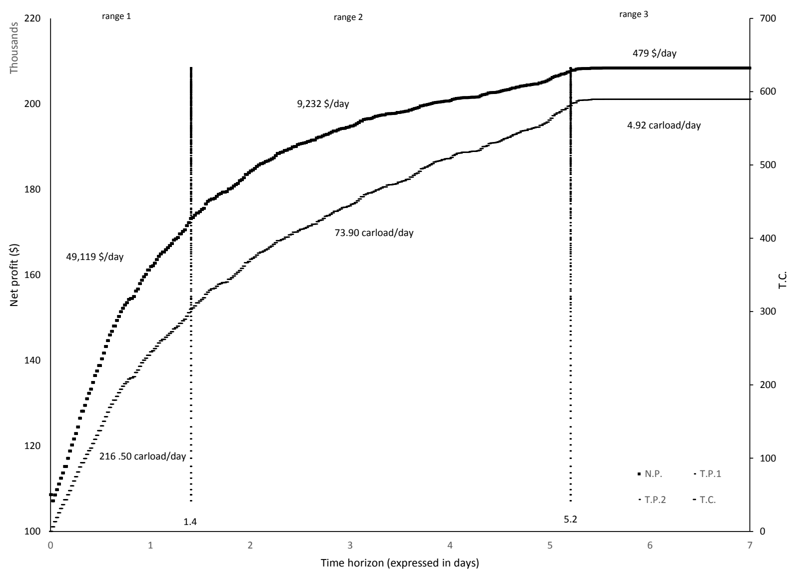


Figure 4.12: Net profit vs. # of carloads.

probably more expensive, and may considerably revise the currently scheduled demands. We also record the average utilization of train services (see Figure 4.14) and train sequences (see Figure 4.15). It also indicates that fewer routing and scheduling alternatives exist for the new coming requests as time moves. Due to the lack of routing and scheduling options at the end of planning, the operator may face difficulty in revising the already scheduled requests that may not only cause less profit margin but also may cause significant increase in risk associated with hazardous materials transportations.

4.5.3 Pricing policies

In an effort to evaluate different pricing policies on the total net profit, we record some performance indicators during the planning horizon before determining the price for the new incoming request. Figure 4.16 together with Table 4.8 shows various pricing policies as a function of time. Figure 4.18 depicts the increases in shipping prices as a function of time together with the total hazardous materials for *Train* pricing policy. Similarity,

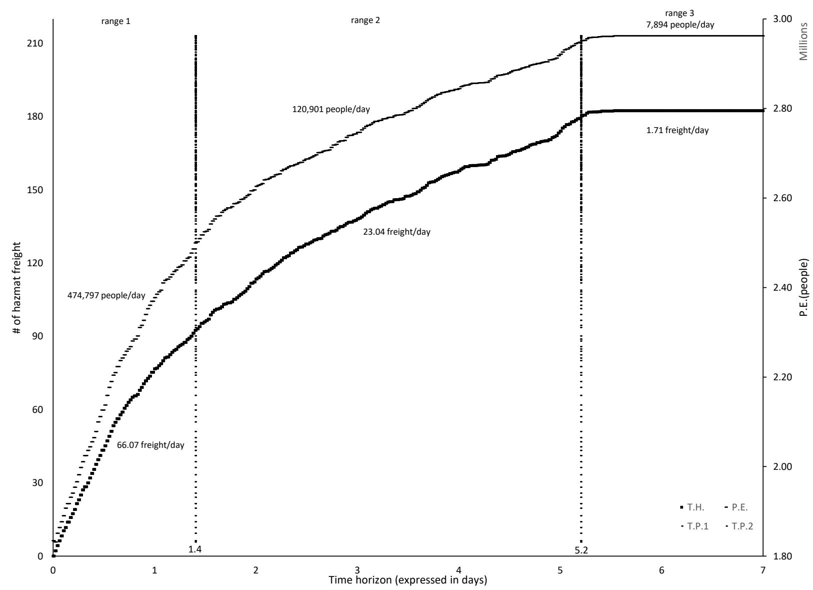


Figure 4.13: Population exposure vs. # hazmat freights.

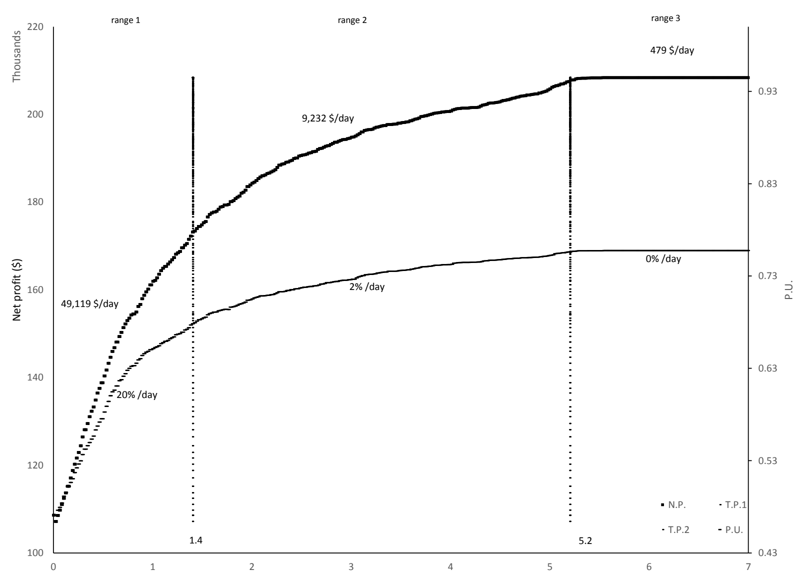


Figure 4.14: Net profit vs. utilization (train sequences).

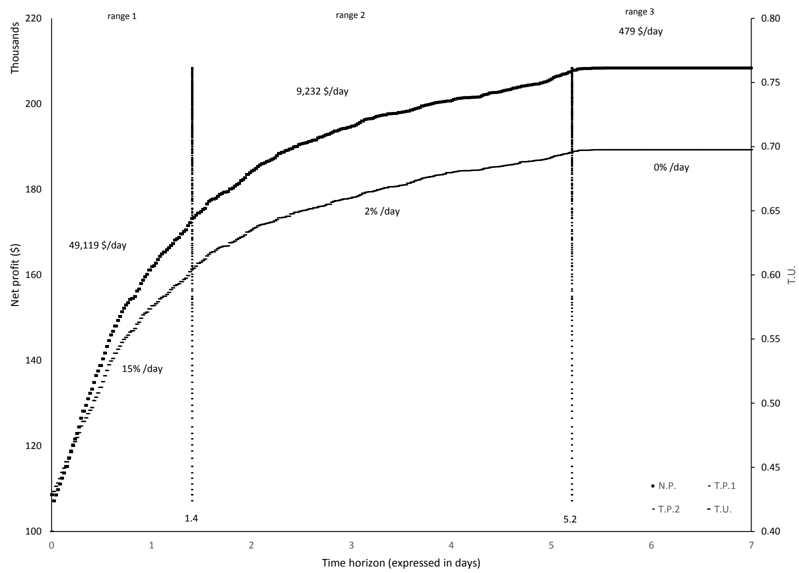


Figure 4.15: Net profit vs. utilization (train services)

Figure 4.19 and Figure 4.20 show the increases in shipping rates as a function of time together with the total hazardous materials for *OD* and *Path* pricing policies. Figure 4.21 depict the average increases in shipping rates as a function of time for all pricing policies. It is clear from Figure 4.21 that the maximum revenue efforts may be pursued as the operator may divide the planning horizon time T into t periods accounting for price increases as the cutoff times approaches. One may divide the planning horizon into three ranges (or more), gradual increases in shipping cost from $t = 0$ to $t = 1.4$, dramatic increases between $t = 1.4$ to $t = 5.2$, and very little after $t = 5.2$. At the first period, adding the demand to the current train services is feasible and profitable as only additional fuel and equipment are needed as the operator has more options in revising the routing and schedule of the already scheduled demand. In the second period, the existing itineraries may need to be revised causing the increased cost of transporting the already existing scheduled freights and significant increases in population exposure.

As we can see both *OD* and *Path* pricing strategies generate the maximum net profit compared to other pricing strategies. The reason for the better performance of OD and *path* pricing policies compared to $Train$ pricing policy could be explained by analyzing the performance indicators for determining the pricing decisions. $Train$ pricing policy determines the pricing of the new incoming request based on the remaining capacity on the train services and the additional risks exposed from hazard shipments. Once the average utilization of the train services exceeds a particular threshold, the operator will increase the price to their customers. This principle was supposed to guide the management on the best time to start their negotiation process with their customers. However, the simplification from using the average train utilization was not enough to give the operator the status of the railway network. Rail operation process is more complex than other transportation, i.e., road or airline transport. Train services are high interrelated, adding or removing some loads from a particular train service will impact the whole capacity of the railway and risks exposed to population from hazard shipments. With analogous considerations, both OD and $Path$ pricing strategies measures the interaction between the remaining capacity of train services and risk threshold associated with hazardous materials to determine the price of the incoming requests. This provides OD and $Path$ pricing strategies with a good indicator to start rising the shipping price for the new incoming demands. Increasing the shipping rates and the introduction of surcharge may reduce the operational burden associated with the transportation of hazardous materials commodities. That is, the additional costs from rerouting the commodities can be compensated by the increasing the shipping rates. The development of an optimization tool to give the decision-maker guidance regarding the delivery and price quotations is a challenging task but an important step in a negotiation process.

Table 4.8: Different pricing strategies.

P.I./Strategy	*Base pricing*				*OD pricing*				*Path pricing*				*Train pricing*			
Range	r_1	r_2	r_3	$\overline{r}$	r_1	r_2	r_3	$\overline{r}$	r_1	r_2	r_3	$\overline{r}$	r_1	r_2	r_3	$\overline{r}$
T.P.	0−1.4	1.4−5.2	5.2−7		0−3	3−5.4	5.4−7		0−3	3−5.4	5.4−7		0−1.4	1.4−5.2	5.2−7	
N.P.	49.12	9.23	0.48	14.93	43.38	10.86	0.06	18.64	42.81	12.43	0.04	18.39	63.90	18.40	0.86	14.99
P.E.	474.80	120.90	78.94	95.63	292.66	87.99	0.59	129.49	306.40	96.84	0.59	135.79	449.10	272.16	9.26	239.95
I.D.	9.93	2.08	0.00	3.11	4.76	0.00	0.00	2.04	5.24	0.00	0.00	2.25	12.54	1.19	0.00	2.51
T.H.	66.07	23.04	1.71	26.10	48.47	20.19	0.14	20.99	45.44	19.18	0.07	19.58	71.51	25.07	2.21	22.04
T.C.	216.50	73.90	4.92	84.48	145.59	60.21	0.28	63.72	148.32	63.02	0.21	64.60	209.13	75.48	6.51	110.42
T.U.	15.00	2.00	0.00	4.04	8.41	1.61	0.00	3.60	8.71	1.64	0.00	3.73	14.20	2.39	0.15	2.89
P.U.	19.88	2.07	0.08	5.11	10.54	1.22	0.00	4.52	10.93	1.24	0.00	4.68	19.45	1.96	0.11	3.92

P.I.: Performance indicator; *T.P.*: Turning points; *N.P.*: Net profit (in 1000's $); *P.E.*: Population exposure (in 1000's people);
I.D.: # of shipment's itinerary; *T.H.*: Total additional hazmat freights (carloads);
T.C.: Total additional freights (carloads); *T.U.*: Train utilization (%); *P.U.* Train sequences utilization(%).

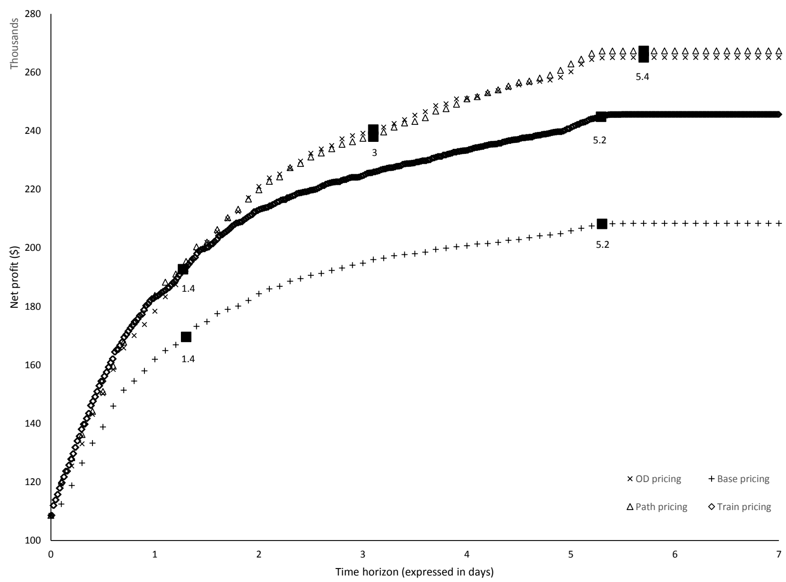


Figure 4.16: Different pricing strategies.

4.5.4 Capacity allocation strategies

One strategy of particular interest is the degree of flexibility in allocation the incoming requests. As mention earlier, the operator may adopt the itinerary of the demands as information revealed to enhance the overall performance. To study the impact of degree of flexibility on the net profit, we study three capacity allocation strategies, refer to as Origin, Enroute, and Full capacity allocation strategy, respectively. The main idea of those capacity allocation strategies is to reallocate some demands from train services facing imminent shortage to another train services with abundant capacity in the favor of the new coming requests. Those strategies are different in the way the itinerary replanning problem is solved. The Origin capacity allocation strategy allows the demand to be rescheduled by assigning the demand to another alternative itinerary at it's origin terminal before the classification process starts, whereas the Enroute capacity allocation policy allows the itinerary replanning at any terminal along it's last published itinerary. The integration of the two kind of itinerary re-planning is investigated in Full capacity allocation strategy.

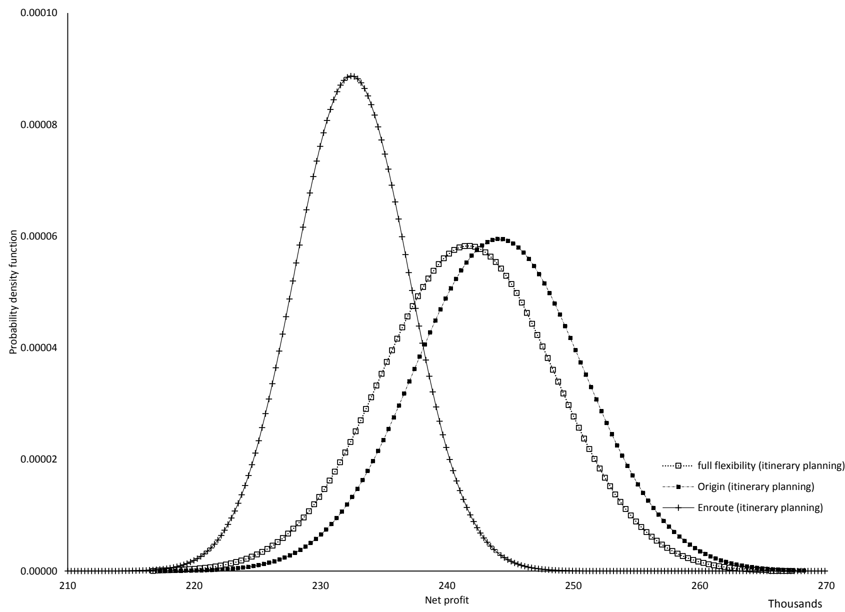


Figure 4.17: Probability distribution function.

Figure 4.17 depicts the net profit for various capacity allocation strategies. It is clear that the profit generated from Origin, and Full capacity allocation strategy are higher than the one produced by Enroute capacity allocation strategy. The reason of the better performance of Origin and Full with respect to Enroute capacity allocation strategy could be justified by the number of alternative itineraries in each strategy. The Enroute capacity allocation strategy is only limited the replanning process at any terminal along the route. This was supposed to generate an efficient number of feasible itineraries. However, the number of alternative itinerary was insufficient for performing local searches. For example, there is only 738 possible moves for the given train sequences. The ability to explore the neighborhood seem not be very extend. With analogues considerations, the Origin capacity allocation strategy contains of 1681 additional itineraries, whereas the Full capacity allocation allows the two type of moves. We report the result of those capacity allocation strategies in Table 4.9 together with results when all the information of the requests are given at beginning of the planning. It is clear that increasing the ability of the operator to allocate the incoming requests to the limited capacity may generate up to 5.03% increases in the net profit with only 2.3% increases on the average train utilization. Such increases in the net profit is significant when dealing with major railway company generates benefits from serving demands of the order of several million dollars. The decision-making process with capacity allocation strategy yields high performances. More importantly, the increases in the net profit generated from adopting those strategies cause insignificant increases on the transport risk (up to 0.35%).

Table 4.9: Different capacity allocation strategies.

Information	*Perfect*			*Imperfect*			I/P^*		
P.I./Strategy	*Enroute*	*Origin*	*Full*	*Enroute*	*Origin*	*Full*	I_1/P_1	I_2/P_2	I_3/P_3
Net profit	292312	303487	306076	232457	244116	244143	0.75	0.79	0.79
std	4010.85	5018.48	7359.49	4496.83	6702.85	6846.61	0.61	0.91	0.93
Risk	3746810	3815800	3846587	3195543	3207087	3185557	0.83	0.83	0.82
std	97206.89	54204.14	85524.16	70607.51	85653.85	96526.38	0.82	1.00	1.12
R	704.80	702.93	717.45	489.43	515.71	513.11	0.68	0.72	0.72
std	33.86	31.71	31.91	29.09	28.17	27.57	0.91	0.88	0.86
H	353.2	354.53	357.09	244.29	157.91	258.74	0.68	0.44	0.72
std	12.96	16.11	15.57	13.26	60.91	15.94	0.85	3.9	1.02
Iti. deviate	–	–	–	20.57	261.47	147.91	–	–	–
std	9.44	34.12	50.66	7.09	17.62	49.56	0.14	0.35	0.97
U_1	0.911	0.922	0.926	0.7593	0.7768	0.7694	0.82	0.84	0.83
std	0.009	0.012	0.012	0.0135	0.0138	0.0182	1.12	1.15	1.52
U_2	0.945	0.952	0.9548	0.8099	0.8263	0.8214	0.84	0.87	0.86
std	0.006	0.008	0.008	0.0126	0.0118	0.0164	1.58	1.48	2.05

*Percent between perfect to imperfect information.

We also evaluate one of the capacity allocation strategy with the most commonly used strategies in North American's railway industry, i.e., First come first served (FCFS). In the $FCFS$ strategy, a request is being assigned to the earliest available train as long as the capacity is available, whereas the second strategy, refereed to as $FCFS2$, is similar to $Full$ policy except that the strategy is not allowed to reschedule the demands during the planning horizon. It is obvious from Table 4.10 that adopting $Full$ capacity allocation strategy will increase the net profit by 12.05% than $FCFS$ with average increases in the population exposure by 3.18%. Such strategy give the carrier full flexibility to reallocate low priority loads to another train sequences to make space for highly priority request, without breaking their delivery quotations.

Table 4.10: Capacity allocation vs. FCFS strategy.

$P.I./Strategy$	$Full$	$FCFC$	$FCFC2$	$Full/FCFC$	$FCFC2/FCFC$
$Net\ profit$	309526	276248	290494	1.12	1.05
std	13876.64	14316.32	11504.33	0.97	0.80
$Risk$	3219595	3120219	3127119	1.03	1.00
std	104429.45	84053.81	86888.49	0.03	1.03
R	509.40	477.10	486.30	1.07	1.00
std	46.74	25.64	25.70	1.82	0.55
H	255.7	240.2	241.8	6.45	0.66
std	19.01	9.39	18.05	1.06	0.95
$Iti.\ deviate$	117.8	–	–	–	–
std	34.32	–	–	–	–
U_1	0.776	0.745	0.753	1.04	1.01
std	0.015	0.013	0.014	1.15	1.08
U_2	0.828	0.798	0.803	1.03	1.01
std	0.012	0.012	0.011	1.00	0.91

4.6 Conclusion

In this chapter, we introduce hazardous material trip plan problem with pricing decisions. The planning procedure was divided into two phases. In the first phase, we solve a deterministic rail freight transportation and train timetabling problem. The solution determines the best request-itinerary assignment decisions in addition to the schedules of the train services. In the second phase, an optimization-based problem is built and solved at the arrival of the new request. The procedure was used to study four pricing strategies in the presence of hazardous materials. The experiment results revealed pricing strategies based on the capacities of train services and population exposure perform very well. The OD and $path$ pricing strategies will provide an average of 8.33% additional profit than $train$ pricing strategy. Increasing the shipping rates and the introduction of surcharge reduce the operational burden associated with the transportation of hazardous materials commodities. That is, the additional costs from rerouting the commodities can be compensated by the increasing the shipping rates.

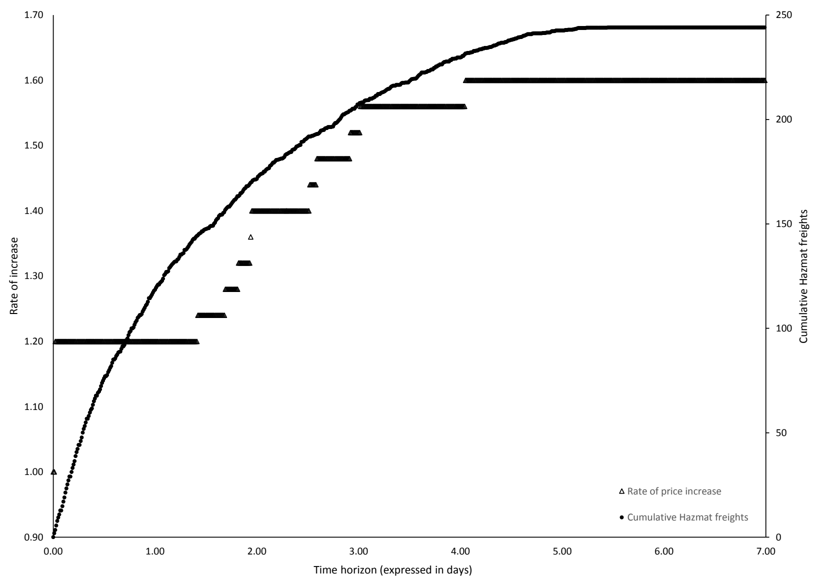


Figure 4.18: Train pricing (Rate of charge).

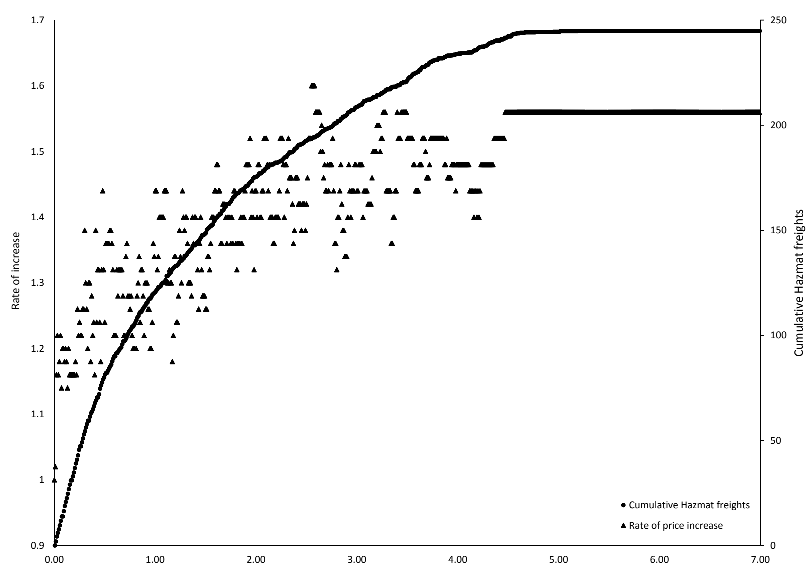


Figure 4.19: OD pricing (Rate of charge).

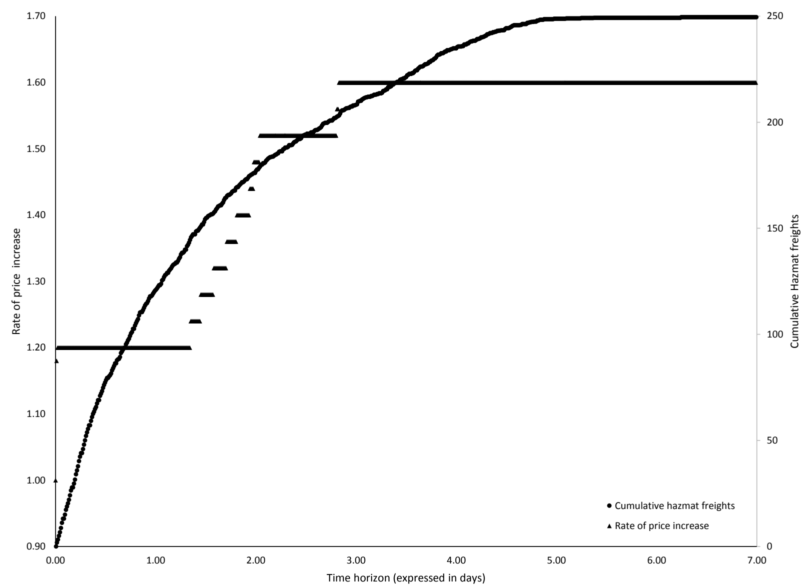


Figure 4.20: Path pricing (Rate of charge).

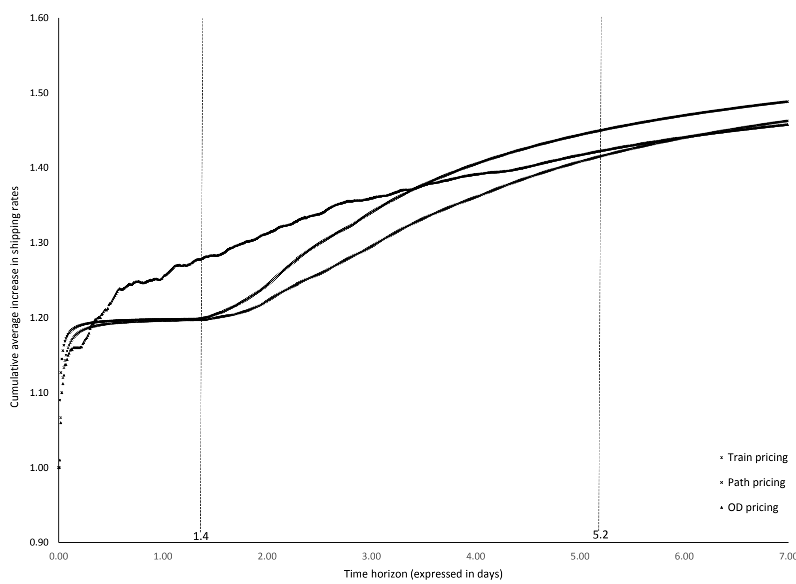


Figure 4.21: Average shipping rate.

Chapter 5

Conclusions and future research recommendations

5.1 Summary of the contents

In this dissertation we studied three versions of *Hazardous Materials Trip plan Problems* (HTPs). In the first part of this dissertation we proposed a compact mathematical model to integrate the blocking and train makeup decisions into trip plan generation process. Solving the HTPs with blocking decisions determines a comprehensive operational plan to provide the required services to customers and to minimize total cost from serving the demands while the transport risk below the given thresholds. We used of aggregate measures of risk, i.e., population exposure and environmental impacts. The solution of the problem specifies for each request (a) the route that must follow from its origin to destination (if the shipment served) (b) the sequence of trains that it will be shipped along the route, and (c) the blocks used to transport it for each train leg along its route. Two matheuristic methods were proposed to solve the considered problem. We also proposed an alternative formulation for the considered problem and a heuristic method by decomposing the problem into freight-to-block and block-to-train assignment problems to solve real size problem instances. Through computational experiments, it may be concluded that the MIP heuristics provide good solutions for realistic size instances while solving the mixed integer programming formulation can be computationally expensive. Comparing the two proposed MIP heuristics, the results demonstrated that BH outperforms the SH solutions for large instances with a large number of train services, on average percent deviations of 26.35% and average of 13.29% less computational time.

The second part of this dissertation proposed a mathematical model that integrates train scheduling decisions into trip plan generation process considering different risk spreading functions. We studied the problem of minimizing the weighted sum of the cost of serving the commodities plus risk distribution function using well-defined measures while constraining the population exposure below the given risk thresholds. The solution of the problem is to determine for each demand (a) the route that must be followed (if not outsourced) including the blocking path, (b) the sequence of trains that it must assign along the route so that the trains capacities constraints, and risk thresholds are satisfied, and also determines the timetable of planned services. Non-linear mixed integer programming models and a heuristic method were proposed for preparing the shipment plans and determining the schedule of train services. The experiment results indicated that considering risk distribution function into trip plan generation may not only have to incur additional financial costs for the carrier but also increases the total risk. To be specific, some requests considerably deviated from the shortest path with an average of 16.29%, causing increases in the total transport risk by 39.78%. Experiment results also revealed that the carrier can achieve a high level of risk distribution by integrating train scheduling decisions into trip plan generation process. More precisely, holding commodities at some terminals represents the opportunity of demands flows to be temporarily stored at terminals along their itinerary to be picked up by less risky train services passing by at later times. This could be achieved by adding some slack times between different train services.

In the last part of this dissertation we studied a freight car scheduling and train dispatching problem involving hazmat transportation. In the considered problem, customer requests known in advance will be scheduled first. Additional requests, after the preliminary schedule is generated, may be scheduled from new customers. Depending on available capacities, the total transport risk and customer requirements, new customers may be quoted with different prices and time to deliver. A two-phase heuristic solution method was developed to solve the considered problem. In some cases, adding the demand to the current train services is feasible and profitable as only additional fuel and equipment are needed, i.e. in the first quarter of the planning. In other cases, the existing itineraries may need to be frequently revised causing the increased cost of transporting the already existing scheduled freights. Or, some of the new requests must be rejected as it becomes infeasible. The procedure was used to study four pricing strategies in the presence of hazardous materials. The experiment results indicated that pricing strategies based on the capacities of train services and population exposure perform very well with other strategies. In particular, the *OD* and *path* pricing strategies will provide an average of 8.33% additional profit than *train* pricing strategy. Increasing the shipping rates and the introduction of additional charges may reduce the operational burden associated with the transportation of hazardous materials commodities.

5.2 Recommendations for future research

Naturally, there exist several aspects related to this research to be further explored that are unfortunately out of the scope of this dissertation. We briefly describe some research avenues for each variant of HTPs studied in this dissertation. First, the research in HTPs with blocking could be enhanced in various ways:

- One enhancement is to investigate the position of hazmat freights in a block and sequence of blocks in train service. In particular, there is a need to develop more sophisticated analytical approaches that generate the routing plans that explicitly consider blocking, and the location of hazmat freights in a block.
- Another enhancement would be to incorporate the risk that arises when a shipment changes a service at a terminal. Such a risk may trade-off against other costs, i.e., tardiness, earliness, etc.

Second, the study in HTPs with train scheduling could be also improved in various ways.

- One improvement is to design a heuristic based on the extension of the standard k-shortest path algorithm to solve the freight transportation problem with risk spreading considerations.
- Another interesting investigation is to incorporate the risk from holding commodities at terminals along their itinerary. Such risk may reduce the benefits from holding commodities at terminals to distribute the risk. We assumed that probability for a shipment releases during storage be zero in our approach. This may not true, there is still a chance of releases of its materials due to crashing or insecure facility conditions.

Finally, the research in HTPs with pricing decision could be enhanced in many ways.

- One enhancement is to investigate other pricing strategies. For instance, the pricing strategy with some probabilistic knowledge of the future and unknown demands is expected to perform very well similar to that in Wang et al. (2016).
- Another possible extension is introduce another group of customers in which partial of their demands could be satisfied.
- We are currently working on more sophisticated extensions of HTPP in which we consider the price of the competitors and the reaction of the customers. The problem could be model as bi-level mathematical formulation, where the first level is a rail carrier and the second level is a group of customers. The leader determines the toll settings for the transit of commodities while considering the reaction of all customers aiming at reducing the total population exposure and risk spreading. Differently than HTPs with pricing decisions, the customers choose their itineraries and the carrier impose tolls on the available itineraries. The regulator identifies a toll policy that minimizes the total population exposure and maximizing the risk spreading, taking into account that the customers follow least-cost route decisions.

Bibliography

Abkowitz, M., Lepofsky, M., and Cheng, P. (1992). Selecting criteria for designating hazardous materials highway routes. *Transportation Research Record*, 1333(2.2).

Abuobidalla, O., Chen, M., and Chauhan, S. (2019a). Hazardous materials trip plan problem with pricing decisions. *Manuscript submitted for publication. Research in Transportation Business & Management.*

Abuobidalla, O., Chen, M., and Chauhan, S. (2019b). An integrated train scheduling and hazardous materials trip planning problem. *Manuscript submitted for publication. International Journal of Rail Transportation.*

Abuobidalla, O., Chen, M., and Chauhan, S. (2019c). A matheuristic method for planning railway freight transportation with hazardous materials. *Journal of Rail Transport Planning & Management*, 10:46–61.

Ahuja, R. K., Goodstein, J., Mukherjee, A., Orlin, J. B., and Sharma, D. (2007a). A very large-scale neighborhood search algorithm for the combined through-fleet-assignment model. *INFORMS Journal on Computing*, 19(3):416–428.

Ahuja, R. K., Jha, K. C., and Liu, J. (2007b). Solving real-life railroad blocking problems. *Interfaces*, 37(5):404–419.

Akgün, V., Erkut, E., and Batta, R. (2000). On finding dissimilar paths. *European Journal of Operational Research*, 121(2):232–246.

Altner, D. S., Ahuja, R. K., Ergun, Ö., and Orlin, J. B. (2014). Very large-scale neighborhood search. In *Search Methodologies*, pages 339–367. Springer.

Anghinolfi, D., Paolucci, M., Sacone, S., and Siri, S. (2011). Freight transportation in railway networks with automated terminals: A mathematical model and mip heuristic approaches. *European Journal of Operational Research*, 214(3):588–594.

Archetti, C. and Speranza, M. G. (2014). A survey on matheuristics for routing problems. *EURO Journal on Computational Optimization*, 2(4):223–246.

Armstrong, A. and Meissner, J. (2010). Railway revenue management: overview and models.

Arya, S. P. et al. (1999). *Air pollution meteorology and dispersion*, volume 310. Oxford University Press New York.

Assadipour, G., Ke, G. Y., and Verma, M. (2015). Planning and managing intermodal transportation of hazardous materials with capacity selection and congestion. *Transportation Research Part E: Logistics and Transportation Review*, 76:45–57.

Assadipour, G., Ke, G. Y., and Verma, M. (2016). A toll-based bi-level programming approach to managing hazardous materials shipments over an intermodal transportation network. *Transportation Research Part D: Transport and Environment*, 47:208–221.

Azad, N., Hassini, E., and Verma, M. (2016). Disruption risk management in railroad networks: An optimization-based methodology and a case study. *Transportation Research Part B: Methodological*, 85:70–88.

Bagheri, M., Saccomanno, F., Chenouri, S., and Fu, L. (2011). Reducing the threat of in-transit derailments involving dangerous goods through effective placement along the train consist. *Accident Analysis & Prevention*, 43(3):613–620.

Bagheri, M., Saccomanno, F., and Fu, L. (2012). Modeling hazardous materials risks for different train make-up plans. *Transportation Research Part E: logistics and transportation review*, 48(5):907–918.

Bagheri, M., Verma, M., and Verter, V. (2014). Transport mode selection for toxic gases: rail or road? *Risk Analysis*, 34(1):168–186.

Barnhart, C., Jin, H., and Vance, P. H. (2000). Railroad blocking: A network design application. *Operations Research*, 48(4):603–614.

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

Bell, M. G. (2006). Mixed route strategies for the risk-averse shipment of hazardous materials. *Networks and Spatial Economics*, 6(3-4):253–265.

Bell, M. G. (2007). Mixed routing strategies for hazardous materials: Decision-making under complete uncertainty. *International Journal of Sustainable Transportation*, 1(2):133–142.

Beroggi, G. E. (1994). A real-time routing model for hazardous materials. *European Journal of Operational Research*, 75(3):508–520.

Bersani, C., Papa, F., Sacile, R., Sallak, M., and Terribile, S. (2016). Towards dynamic exposure-based schedule for hazardous material trains. *Journal of Rail Transport Planning & Management*, 6(2):116–127.

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.

Bianco, L., Caramia, M., Giordani, S., and Piccialli, V. (2012). A game theory approach for regulating hazmat transportation. Technical report, Tech. Rep. RR-21.12, Dipartimento di Ingegneria dell'Impresa.

Bilegan, I. C., Brotcorne, L., Feillet, D., and Hayel, Y. (2015). Revenue management for rail container transportation. *EURO Journal on Transportation and Logistics*, 4(2):261–283.

Bock, S. (2010). Real-time control of freight forwarder transportation networks by integrating multimodal transport chains. *European Journal of Operational Research*, 200(3):733–746.

Boschetti, M. A., Maniezzo, V., Roffilli, M., and Röhler, A. B. (2009). Matheuristics: Optimization, simulation and control. In *International Workshop on Hybrid Metaheuristics*, pages 171–177. Springer.

Branscomb, L., Fagan, M., Auerswald, P. E., Ellis, R., and Barcham, R. (2010). Rail transportation of toxic inhalation hazards: Policy responses to the safety and security externality. *Available at SSRN 2397482*.

Branscomb, L. M., Ellis, R. N., and Fagan, M. (2012). Between safety and security: The policy challenges of transporting toxic inhalation hazards. *Journal of Homeland Security and Emergency Management*, 9(2).

Cacchiani, V., Caprara, A., and Toth, P. (2008). A column generation approach to train timetabling on a corridor. *4OR*, 6(2):125–142.

Cai, X., Sha, D., and Wong, C. (2001). Time-varying minimum cost flow problems. *European Journal of Operational Research*, 131(2):352–374.

Calvo, F. and De Oña, J. (2012). Are rail charges connected to costs? *Journal of Transport Geography*, 22:28–33.

Campbell, K. C. (1996). Booking and revenue management for rail intermodal services. thesis, department of systems engineering.

Cao, C., Gao, Z., and Li, K. (2012). Capacity allocation problem with random demands for the rail container carrier. *European Journal of Operational Research*, 217(1):214–221.

Caprara, A., Fischetti, M., and Toth, P. (2002). Modeling and solving the train timetabling problem. *Operations research*, 50(5):851–861.

Caprara, A., Monaci, M., Toth, P., and Guida, P. L. (2006). A lagrangian heuristic algorithm for a real-world train timetabling problem. *Discrete applied mathematics*, 154(5):738–753.

Carotenuto, P., Giordani, S., and Ricciardelli, S. (2007). Finding minimum and equitable risk routes for hazmat shipments. *Computers & Operations Research*, 34(5):1304–1327.

Chang, E., Floros, E., and Ziliaskopoulos, A. (2007). An intermodal time-dependent minimum cost path algorithm. In *Dynamic Fleet Management*, pages 113–132. Springer.

Chang, T.-S. (2008). Best routes selection in international intermodal networks. *Computers & operations research*, 35(9):2877–2891.

Cheng, J., Verma, M., and Verter, V. (2017). Impact of train makeup on hazmat risk in a transport corridor. *Journal of Transportation Safety & Security*, 9(2):167–194.

Chin, S.-M., Hwang, H.-L., Peterson, B. E., Han, L. D., and Chin, C. (2009). Routing hazardous materials around the district of columbia area. *Journal of Transportation*

Safety & Security, 1(4):296–313.

CN (2019). Prices, tariffs & transit timesa.

Cordeau, J.-F., Toth, P., and Vigo, D. (1998). A survey of optimization models for train routing and scheduling. *Transportation science*, 32(4):380–404.

Côté, J.-P., Marcotte, P., and Savard, G. (2003). A bilevel modelling approach to pricing and fare optimisation in the airline industry. *Journal of Revenue and Pricing Management*, 2(1):23–36.

Cox, R. G. and Turnquist, M. A. (1986). *Scheduling truck shipments of hazardous materials in the presence of curfews*. Number 1063.

Crainic, T., Ferland, J.-A., and Rousseau, J.-M. (1984). A tactical planning model for rail freight transportation. *Transportation science*, 18(2):165–184.

Crainic, T. G. (2000). Service network design in freight transportation. *European Journal of Operational Research*, 122(2):272–288.

Crevier, B., Cordeau, J.-F., and Savard, G. (2012). Integrated operations planning and revenue management for rail freight transportation. *Transportation Research Part B: Methodological*, 46(1):100–119.

D'Ariano, A. and Pranzo, M. (2009). An advanced real-time train dispatching system for minimizing the propagation of delays in a dispatching area under severe disturbances. *Networks and Spatial Economics*, 9(1):63–84.

Doerner, K. F. and Schmid, V. (2010). Survey: matheuristics for rich vehicle routing problems. In *International Workshop on Hybrid Metaheuristics*, pages 206–221. Springer.

DOT (2017a). Estimation of unit costs of rail transportation in canada.

DOT (2017b). Hazardous materials shipments by transportation mode.

DOT (2017c). Transportion statistics annual report 2017.

Erkut, E. (1995). Special issue of infor on hazardous materials logistics. *INFOR: Information Systems and Operational Research*, 33(2):65–67.

Erkut, E. and Alp, O. (2007a). Designing a road network for hazardous materials shipments. *Computers & Operations Research*, 34(5):1389–1405.

Erkut, E. and Alp, O. (2007b). Integrated routing and scheduling of hazmat trucks with stops en route. *Transportation Science*, 41(1):107–122.

Erkut, E. and Gzara, F. (2008). Solving the hazmat transport network design problem. *Computers & Operations Research*, 35(7):2234–2247.

Erkut, E. and Ingolfsson, A. (2000). Catastrophe avoidance models for hazardous materials route planning. *Transportation Science*, 34(2):165–179.

Erkut, E., Tjandra, S. A., and Verter, V. (2007). Hazardous materials transportation. *Handbooks in operations research and management science*, 14:539–621.

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

Esfandeh, T., Batta, R., and Kwon, C. (2017). Time-dependent hazardous-materials network design problem. *Transportation Science*, 52(2):454–473.

Even, A. S. S., Itai, A., and Shamir, A. (1976a). On the cimplexity of timetable and multi-commodity how problems. *Journal of Computing*.

Even, S., Itai, A., and Shamir, A. (1976b). On the complexity of timetable and multicommodity flow problems. *SIAM Journal on Computing*, 5(4):691–703.

Fang, K., Ke, G. Y., and Verma, M. (2017). A routing and scheduling approach to rail transportation of hazardous materials with demand due dates. *European Journal of Operational Research*, 261(1):154–168.

Fontaine, P., Crainic, T., Gendreau, M., and Mendoza, J. E. (2016). *Population-based risk equilibration for the multi-mode hazmat transport network design problem*. CIRRELT.

Frank Pasquill, F. B. S. (1983). *Pasquill Atmospheric Diffusion 3ed - Study of the Dispersion of Windborne Material Etc.* Ellis Horwood, Chichester, UK.

Fukasawa, R., de Aragão, M. V. P., Porto, O., and Uchoa, E. (2002). Solving the freight car flow problem to optimality. *Electronic Notes in Theoretical Computer Science*, 66(6):42–52.

Garrido, R. A. (2010). Terrorists and hazmat: a methodology to identify potential routes. In *Security and Environmental Sustainability of Multimodal Transport*, pages 149–166. Springer.

Glickman, T. S. (1983). Rerouting railroad shipments of hazardous materials to avoid populated areas. *Accident Analysis & Prevention*, 15(5):329–335.

Glickman, T. S., Erkut, E., and Zschocke, M. S. (2007). The cost and risk impacts of rerouting railroad shipments of hazardous materials. *Accident Analysis & Prevention*, 39(5):1015–1025.

Goel, A. (2010). The value of in-transit visibility for supply chains with multiple modes of transport. *International Journal of Logistics: Research and Applications*, 13(6):475–492.

Gopalan, R., Kolluri, K. S., Batta, R., and Karwan, M. H. (1990). Modeling equity of risk in the transportation of hazardous materials. *Operations Research*, 38(6):961–973.

Gorman, M. F. (1998). An application of genetic and tabu searches to the freight railroad operating plan problem. *Annals of operations research*, 78:51–69.

Gorman, M. F. (2015). Operations research in rail pricing and revenue management. In *Handbook of Operations Research Applications at Railroads*, pages 243–254. Springer.

Haghani, A. E. (1989). Formulation and solution of a combined train routing and makeup, and empty car distribution model. *Transportation Research Part B: Methodological*, 23(6):433–452.

Hosseini, S. D. and Verma, M. (2017). A value-at-risk (var) approach to routing rail hazmat shipments. *Transportation research part D: transport and environment*, 54:191–211.

Hosseini, S. D. and Verma, M. (2018). Conditional value-at-risk (cvar) methodology to optimal train configuration and routing of rail hazmat shipments. *Transportation Research Part B: Methodological*, 110:79–103.

Huntley, C. L., Brown, D. E., Sappington, D. E., and Markowicz, B. P. (1995). Freight routing and scheduling at csx transportation. *Interfaces*, 25(3):58–71.

Ingolfsson, A. and Erkut, E. (2000). Catastrophe avoidance models for hazardous materials route planning. *Transport Science*, 34(2):165–179.

Ireland, P., Case, R., Fallis, J., Dyke, C. V., Kuehn, J., and Meketon, M. (2004). The canadian pacific railway transforms operations by using models to develop its operating plans. *Interfaces*, 34(1):5–14.

Jabbarzadeh, A., Azad, N., and Verma, M. (2019). An optimization approach to planning rail hazmat shipments in the presence of random disruptions. *Omega*.

Jarocka, M., R. U. (2016). Pricing in the railway transport. *JIn: 9th International Scientific Conference - Business and Management 2016*.

Jha, K. C., Ahuja, R. K., and Şahin, G. (2008). New approaches for solving the block-to-train assignment problem. *Networks: An International Journal*, 51(1):48–62.

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.

Kara, B. Y., Erkut, E., and Verter, V. (2003). Accurate calculation of hazardous materials transport risks. *Operations Research Letters*, 31(4):285–292.

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

Kazemzadeh, M. R. A., Crainic, T. G., and Gendron, B. (2018). A lagrangian-based matheuristic for multilayer single flow-type multicommodity capacitated fixed-charge network design. *Publication CIRRELT-2018-37,Centre interuniversitaire de recherche sur les réseaux d'entreprise, la logistique et le transport, Montréal, Quebec, Canada*.

Keaton, M. H. (1989). Designing optimal railroad operating plans: Lagrangian relaxation and heuristic approaches. *Transportation Research Part B: Methodological*, 23(6):415–431.

Khaled, A. A., Jin, M., Clarke, D. B., and Hoque, M. A. (2015). Train design and routing optimization for evaluating criticality of freight railroad infrastructures. *Transportation Research Part B: Methodological*, 71:71–84.

Koutsopoulos, H. N. and Xu, H. (1993). An information discounting routing strategy for advanced traveler information systems. *Transportation Research Part C: Emerging Technologies*, 1(3):249–264.

Kraay, D. R. and Harker, P. T. (1995). Real-time scheduling of freight railroads. *Transportation Research Part B: Methodological*, 29(3):213–229.

Kraft, E. R. (2002). Scheduling railway freight delivery appointments using a bid price approach. *Transportation Research Part A: Policy and Practice*, 36(2):145–165.

Kuby, M., Zhongyi, X., and Xiaodong, X. (1997). A minimax method for finding the k best "differentiated" paths. *Geographical Analysis*, 29(4):298–313.

Kwon, O. K., Martland, C. D., and Sussman, J. M. (1998). Routing and scheduling temporal and heterogeneous freight car traffic on rail networks. *Transportation Research Part E: Logistics and Transportation Review*, 34(2):101–115.

Li, L., Lin, X., Negenborn, R. R., and De Schutter, B. (2015). Pricing intermodal freight transport services: A cost-plus-pricing strategy. In *International Conference on Computational Logistics*, pages 541–556. Springer.

Li, L. and Tayur, S. (2005). Medium-term pricing and operations planning in intermodal transportation. *Transportation science*, 39(1):73–86.

Li, X., Wei, K., Aneja, Y. P., Tian, P., and Cui, Y. (2017). Matheuristics for the single-path design-balanced service network design problem. *Computers & Operations Research*, 77:141–153.

List, G. F., Mirchandani, P. B., Turnquist, M. A., and Zografos, K. G. (1991). Modeling and analysis for hazardous materials transportation: Risk analysis, routing/scheduling and facility location. *Transportation Science*, 25(2):100–114.

Littlechild, S. C. (1970). Marginal-cost pricing with joint costs. *The Economic Journal*, 80(318):323–335.

Liu, D. and Yang, H. (2015). Joint slot allocation and dynamic pricing of container sea–rail multimodal transportation. *Journal of traffic and transportation engineering (English Edition)*, 2(3):198–208.

Lulli, G., Pietropaoli, U., and Ricciardi, N. (2011). Service network design for freight railway transportation: the italian case. *Journal of the Operational Research Society*, 62(12):2107–2119.

Magnanti, T. L. and Wong, R. T. (1984). Network design and transportation planning: Models and algorithms. *Transportation science*, 18(1):1–55.

Maragos, S. A. (1994). *Revenue management for ocean carriers: optimal capacity allocation with multiple nested freight rate classes*. PhD thesis, Massachusetts Institute of Technology.

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

Margolis, J. (2015). *Runaway Risks: Oil Trains and the Government's Failure to Protect People, Wildlife and the Environment*. Center for Biological Diversity.

Marin, A. and Salmeron, J. (1996). Tactical design of rail freight networks. part i: Exact and heuristic methods. *European journal of operational research*, 90(1):26–44.

McClure, T., Brentlinger, L., Drago, V., and Kerr, D. (1988). Considerations in rail routing of radioactive materials. In *Technical Report, Office of Transport Systems and Planning, Battelle Memorial Institute*.

Miller-Hooks, E. D. and Mahmassani, H. S. (2000). Least expected time paths in stochastic, time-varying transportation networks. *Transportation Science*, 34(2):198–215.

Minoux, M. (1989). Networks synthesis and optimum network design problems: Models, solution methods and applications. *Networks*, 19(3):313–360.

Moccia, L., Cordeau, J.-F., Laporte, G., Ropke, S., and Valentini, M. P. (2008). Modeling and solving a multimodal routing problem with timetables and time windows. *submitted to Networks*.

Moccia, L., Cordeau, J.-F., Laporte, G., Ropke, S., and Valentini, M. P. (2011). Modeling and solving a multimodal transportation problem with flexible-time and scheduled services. *Networks*, 57(1):53–68.

Mohan, M., Panwar, T., and Singh, M. (1995). Development of dense gas dispersion model for emergency preparedness. *Atmospheric Environment*, 29(16):2075–2087.

Nozick, L. K., List, G. F., and Turnquist, M. A. (1997a). Integrated routing and scheduling in hazardous materials transportation. *Transportation Science*, 31(3):200–215.

Nozick, L. K., Morlok, E. K., et al. (1997b). A model for medium-term operations planning in an intermodal rail-truck service. *Transportation research part a: policy and practice*, 31(2):91–107.

Oggero, A., Darbra, R., Munoz, M., Planas, E., and Casal, J. (2006). A survey of accidents occurring during the transport of hazardous substances by road and rail. *Journal of hazardous materials*, 133(1-3):1–7.

Özdamar, L., Ekinci, E., and Küçükyazici, B. (2004). Emergency logistics planning in natural disasters. *Annals of operations research*, 129(1-4):217–245.

Pak, K. and Dekker, R. (2004). Cargo revenue management: Bid-prices for a 0-1 multi knapsack problem.

Powell, W. B., Sheffi, Y., Nickerson, K. S., Butterbaugh, K., and Atherton, S. (1988). Maximizing profits for north american van lines' truckload division: A new framework for pricing and operations. *Interfaces*, 18(1):21–41.

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.

Roberts, J. F. (1978). Common carriers and risk distribution: absolute liability for transporting hazardous materials. *Ky. LJ*, 67:441.

Romero, N., Nozick, L. K., and Xu, N. (2016). Hazmat facility location and routing analysis with explicit consideration of equity using the gini coefficient. *Transportation research part E: logistics and transportation review*, 89:165–181.

Saccomanno, F. and El-Hage, S. (1989). Minimizing derailments of railcars carrying dangerous commodities through effective marshaling strategies. *Transportation Research Record*, 1245(34-51):39–41.

Saccomanno, F. F. and Chan, A.-W. (1985). *Economic evaluation of routing strategies for hazardous road shipments*. Number 1020.

Sarhadi, H., Tulett, D. M., and Verma, M. (2017). An analytical approach to the protection planning of a rail intermodal terminal network. *European Journal of Operational Research*, 257(2):511–525.

Searag, S., Maloney, G., and McKeown, L. (2015). *Trucking dangerous goods in Canada, 2004 to 2012*. Statistics Canada.

Sherali, H. D., Brizendine, L. D., Glickman, T. S., and Subramanian, S. (1997). Low probability—high consequence considerations in routing hazardous material shipments. *Transportation Science*, 31(3):237–251.

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.

Sun, Y., Lang, M., and Wang, D. (2016). Bi-objective modelling for hazardous materials road–rail multimodal routing problem with railway schedule-based space–time constraints. *International journal of environmental research and public health*, 13(8):762.

Szeto, W. Y., Farahani, R. Z., and Sumalee, A. (2017). Link-based multi-class hazmat routing-scheduling problem: A multiple demon approach. *European Journal of Operational Research*, 261(1):337–354.

Tjokroamidjojo, D., Kutanoglu, E., and Taylor, G. D. (2006). Quantifying the value of advance load information in truckload trucking. *Transportation Research Part E: Logistics and Transportation Review*, 42(4):340–357.

Törnquist, J. (2006). Computer-based decision support for railway traffic scheduling and dispatching: A review of models and algorithms. In *5th Workshop on Algorithmic Methods and Models for Optimization of Railways (ATMOS'05)*. Schloss Dagstuhl-Leibniz-Zentrum für Informatik.

Tretheway, M. W. and Waters, W. (1993). Costing the movement of hazardous materials by rail. In *Transportation of Hazardous Materials*, pages 277–294. Springer.

Van Dyke, C. and Meketon, M. (2015). Car scheduling/trip planning. In *Handbook of Operations Research Applications at Railroads*, pages 79–118. Springer.

van Riessen, B., Negenborn, R. R., and Dekker, R. (2017). The cargo fare class mix problem for an intermodal corridor: revenue management in synchromodal container transportation. *Flexible Services and Manufacturing Journal*, 29(3-4):634–658.

Verma, M. (2011). Railroad transportation of dangerous goods: A conditional exposure approach to minimize transport risk. *Transportation research part C: emerging technologies*, 19(5):790–802.

Verma, M. and Verter, V. (2007). Railroad transportation of dangerous goods: Population exposure to airborne toxins. *Computers & operations research*, 34(5):1287–1303.

Verma, M. and Verter, V. (2008). The trade-offs in rail-truck intermodal transportation of hazardous materials: an illustrative case study. *Advanced Technologies and Methodologies for Risk Management in the Global Transport of Dangerous Goods: NATO Science for Peace and Security Series*, 45:148–168.

Verma, M. and Verter, V. (2010). A lead-time based approach for planning rail–truck intermodal transportation of dangerous goods. *European Journal of Operational Research*, 202(3):696–706.

Verma, M., Verter, V., and Gendreau, M. (2011). A tactical planning model for railroad transportation of dangerous goods. *Transportation Science*, 45(2):163–174.

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: logistics and transportation review*, 48(1):132–149.

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

Wang, Y., Bilegan, I. C., Crainic, T. G., and Artiba, A. (2016). A revenue management approach for network capacity allocation of an intermodal barge transportation system. In *International Conference on Computational Logistics*, pages 243–257. Springer.

Xiao, J., Pachl, J., Lin, B., and Wang, J. (2018). Solving the block-to-train assignment problem using the heuristic approach based on the genetic algorithm and tabu search. *Transportation Research Part B: Methodological*, 108:148–171.

Yagiura, M., Iwasaki, S., Ibaraki, T., and Glover, F. (2004). A very large-scale neighborhood search algorithm for the multi-resource generalized assignment problem. *Discrete Optimization*, 1(1):87–98.

Yang, J., Jaillet, P., and Mahmassani, H. (2004). Real-time multivehicle truckload pickup and delivery problems. *Transportation Science*, 38(2):135–148.

You, P.-S. (2008). An efficient computational approach for railway booking problems. *European Journal of Operational Research*, 185(2):811–824.

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

Zhao, J. and Verter, V. (2015). A bi-objective model for the used oil location-routing problem. *Computers & Operations Research*, 62:157–168.

Zhu, E., Crainic, T. G., and Gendreau, M. (2014). Scheduled service network design for freight rail transportation. *Operations research*, 62(2):383–400.

Zografos, K. G. and Androutsopoulos, K. N. (2004). A heuristic algorithm for solving hazardous materials distribution problems. *European Journal of Operational Research*, 152(2):507–519.

Zografos, K. G. and Androutsopoulos, K. N. (2008). A decision support system for integrated hazardous materials routing and emergency response decisions. *Transportation Research Part C: Emerging Technologies*, 16(6):684–703.

Zografos, K. G. and Davis, C. F. (1989). Multi-objective programming approach for routing hazardous materials. *Journal of Transportation engineering*, 115(6):661–673.

Zolfagharinia, H. and Haughton, M. (2014). The benefit of advance load information for truckload carriers. *Transportation Research Part E: Logistics and Transportation Review*, 70:34–54.

Zolfagharinia, H. and Haughton, M. (2016). Effective truckload dispatch decision methods with incomplete advance load information. *European Journal of Operational Research*, 252(1):103–121.

Appendix A

Alternative mathematical model and solution method

Sets and parameters

Before we present the alternative mathematical model and for expositional reasons, we next present a simple example for the HTP with blocking decisions. Figure A.1 depicts a small rail network $G(I,L)$, where $I = \{i_1, i_2, i_3, i_4\}$ and $L = \{l_1, l_2, ..., l_9\}$. The operational characteristics of train services are given in Table A.1, i.e., *train* 2 consists of two service legs l_4 and l_5. Given the definition of an itinerary, the origin and destination pair of block of cars can be met by one of the itineraries given in Table A.2. Information regarding the potential blocks are given in Table A.3. Note that we do not specify the destination of block of cars for flexibility reason. Let P_b be subset of blocking paths that a block b can follow in a solution. For instance, block b_1 can be assigned to any path in the set P_{b_1}, i.e., $P_{b_1} = \{p_1, ..., p_{14}\}$. Let also P_l be subset of paths that traverse along the direct train service l, i.e., $P_{l_5} = \{p_5, p_6, p_{12}, p_{13}, p_{16}, p_{20}\}$. Given the set of itineraries in Table A.2, the pair of direct train service (l, l') is called compatible services if they form a complete path for block of cars from o_l to $d_{l'}$. Let $\bar{\sigma_p}$ be the set of sections for blocking path p. Each section of a blocking path p, $s \in \bar{\sigma_p}$, represents block movement on a service, that is block-to-train assignment. We also introduce parameter $\bar{\alpha}_p^s$ to indicate the sth service of the blocking path p. For instance, the blocking path p_{11} consists of three sections, starts by service $\bar{\alpha}^1_{p_{11}} = 4$ and ends by service $\bar{\alpha}^3_{p_{11}} = 3$. Let $\lambda^{'}$ be the set of compatible pair of services, i.e., $\lambda^{'} = \{(l_1, l_2), (l_1, l_5), ..., (l_5, l_3), (l_8, l_9)\}$. Let also λ be subset of $\lambda^{'}$ that required a train transfer at terminal $i = d_l$, i.e., $\lambda = \{(l_1, l_5), ..., (l_5, l_3)\}$. The process to generate the set of blocking paths is done once and for all in our algorithm, and needs only a few seconds of computation time.

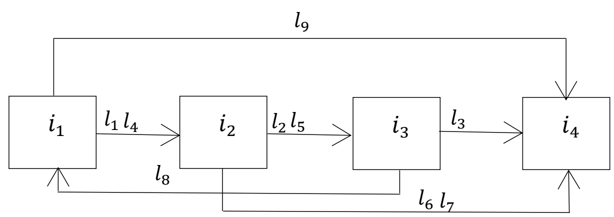


Figure A.1: A simple time schedule network.

We also introduce several sets to reduce the size of the problem by three or four orders of magnitude. Let L_b be the subset of direct services in which a block b can be assigned to, i.e., $L_{b_3} = \{l_2, l_3, l_5, l_6, l_7\}$. Analogously, let L_k denotes the subset of train services in which a demand k can be shipped through. For instance $k_1(i_1, i_4)$, an OD demand pair that is ready at 0.7 time unit and must be shipped no later than 2.8 time unit, can be shipped along any combination of the services in L_{k_1} which form a complete path from i_1 to i_4, $L_{k_1} = \{l_2, l_3, l_4, l_5, l_7, l_9\}$. Furthermore, let B_l be the subset of potential blocks that could be assigned to the direct train service l, i.e., $B_{l_9} = \{b_1, b_2, b_5\}$, whereas B_k be the subset of potential blocks that a commodity k could be part of block of cars, i.e., $B_{k_1} = \{b_1, b_2, b_3, b_4\}$. To consider the blocking limitation at terminal, we introduce set $B(i, t)$ to be the potential blocks of cars being constructed at terminal i at time t. Note that each section of block can be treated as a unique service with certain OD, schedule and capacity.

Figure A.2 (Figure A.3) depicts the $p_1 - p_{14}$ ($p_{15} - p_{23}$) blocking paths over the planning time T. For instance, a blocking path p_{11} occupies a track at i_1 from 0.3 to 0.9 unit time, travels along direct train service l_4, holds a track at i_2 from 1.2 to 1.4 unit time, hauls along direct train service l_2, holds a track at i_3 from 1.9 to 2.2 unit time, and pulls along direct train service l_3.

It is obvious that once a rail network, shipment requirements and candidate blocks are given, the definition of P_b, P_l, λ, λ', L_b, L_{k_1} and B_k are fixed.

Table A.1: Timetable of the train services with the atmospheric class.

Train #	*Itinerary*	τ_l^O			τ_l^C			τ_l^D			τ_l^A		
-	-	s_1	s_2	s_3	s_1	s_2	s_3	s_1	s_2	s_3	s_1	s_2	s_3
train 1	$i_1 \xrightarrow[C]{l_1} i_2 \xrightarrow[E]{l_2} i_3 \xrightarrow[B]{l_3} i_4$	0.0	0.8	1.6	0.5	1.3	2.1	0.6	1.4	2.2	0.9	1.9	2.5
train 2	$i_1 \xrightarrow[D]{l_4} i_2 \xrightarrow[F]{l_5} i_3$	0.3	1.0	-	0.8	1.5	-	0.9	1.6	-	1.2	2.1	-
train 3	$i_2 \xrightarrow[B]{l_6} i_4$	0.5	-	-	1.0	-	-	1.1	-	-	1.6	-	-
train 4	$i_2 \xrightarrow[F]{l_7} i_4$	0.7	-	-	1.3	-	-	1.4	-	-	1.8	-	-
train 5	$i_3 \xrightarrow[C]{l_8} i_1 \xrightarrow[D]{l_9} i_4$	1.3	1.9	-	1.8	2.4	-	1.9	2.5	-	2.4	2.8	-

Table A.2: All possible OD paths.

$i_1 \rightarrow i_2$	$i_1 \rightarrow i_3$	$i_1 \rightarrow i_4$	$i_2 \rightarrow i_3$	$i_2 \rightarrow i_4$	$i_3 \rightarrow i_1$	$i_3 \rightarrow i_4$
$p_1 : i_1 \xrightarrow{l_1} i_2$	$p_3 : i_1 \xrightarrow{l_1} i_2 \xrightarrow{l_2} i_3$	$p_7 : i_1 \xrightarrow{l_1} i_2^* \xrightarrow{l_6} i_4$	$p_{15} : i_2 \xrightarrow{l_2} i_3$	$p_{17} : i_2 \xrightarrow{l_6} i_4$	$p_{21} : i_3 \xrightarrow{l_8} i_1$	$p_{22} : i_3 \xrightarrow{l_3} i_4$
$p_2 : i_1 \xrightarrow{l_4} i_2$	$p_4 : i_1 \xrightarrow{l_4} i_2^* \xrightarrow{l_2} i_3$	$p_8 : i_1 \xrightarrow{l_1} i_2^* \xrightarrow{l_7} i_4$	$p_{16} : i_2 \xrightarrow{l_5} i_3$	$p_{18} : i_2 \xrightarrow{l_7} i_4$		$p_{23} : i_3 \xrightarrow{l_8} i_1 \xrightarrow{l_9} i_4$
	$p_5 : i_1 \xrightarrow{l_1} i_2^* \xrightarrow{l_5} i_3$	$p_9 : i_1 \xrightarrow{l_4} i_2^* \xrightarrow{l_7} i_4$		$p_{19} : i_2 \xrightarrow{l_2} i_3 \xrightarrow{l_3} i_4$		
	$p_6 : i_1 \xrightarrow{l_4} i_2 \xrightarrow{l_5} i_3$	$p_{10} : i_1 \xrightarrow{l_1} i_2 \xrightarrow{l_2} i_3 \xrightarrow{l_3} i_4$		$p_{20} : i_2 \xrightarrow{l_5} i_3^* \xrightarrow{l_3} i_4$		
		$p_{11} : i_1 \xrightarrow{l_4} i_2^* \xrightarrow{l_2} i_3 \xrightarrow{l_3} i_4$				
		$p_{12} : i_1 \xrightarrow{l_1} i_2^* \xrightarrow{l_5} i_3^* \xrightarrow{l_3} i_4$				
		$p_{13} : i_1 \xrightarrow{l_4} i_2 \xrightarrow{l_5} i_3^* \xrightarrow{l_3} i_4$				
		$p_{14} : i_1 \xrightarrow{l_9} i_4$				

i^* required a train change at terminal i

Table A.3: Characteristics of blocks.

B	b_1	b_2	b_3	b_4	b_5
o_b	i_1	i_1	i_2	i_2	i_3

With the subsequent model declarations, the following abbreviations are used: $[-]$, i.e., without any base unit; $[MU]$, i.e., monetary units; $[TU]$, i.e., time units; $[PU]$, i.e., population density units; $[VU]$, i.e., volume units; $[QU]$, i.e., quantity units; $[DU]$, i.e., distance units; $[AU]$, i.e., area units.

I	Set of railway terminals, index by i or $j \in I$.[−]
L	Set of direct train services, index by l or $l' \in L$.[−]
K	Set of requests, index by $k \in K$.[−]
$\mathcal{F}$	Subset of requests that must be served by the carrier $\mathcal{F} \subset K$.[−]
B	Set of potential blocks of cars, index by $b \in B$.[−]
L_b	Subset of train services in which a block b can be assigned to, index by $l \in L_b$.[−]
L_k	Subset of train services in which a demand k can be shipped through, index by $l \in L_k$.[−]
L_j^+	Subset of emanating direct train services from yard j, i.e., $L_j^+ = \{l \in L \mid o_l = j\}$.[−]
L_j^-	Subset of train services terminates at yard j, i.e., $L_j^- = \{l \in L \mid d_l = j\}$.[−]
B_l	Subset of potential blocks that could be assigned to train service l, index by $b \in B_l$.[−]
B_k	Subset of potential blocks in which a request k can be assigned to, index by $b \in B_k$.[−]
T	Set of time instants during the planning horizon $\|T\|$, index by $t \in T$.[−]
$B(i,t)$	Set of potential blocks of cars being constructed at terminal i at time t, index by $b \in B(i,t)$.[−]
P_b	Set of all possible paths to route block b including the train services it is assigned along that path, index by $p \in P_b$.[−]
P	Set of all paths to route all potential blocks in set B, i.e., $P = \bigcup_{b \in B} P_b$.[−]
$\bar{\sigma_p}$	Set of sections for the blocking path p, index by $s \in \bar{\sigma_p}$. [−]
$\bar{\alpha}_p^s$	Integer represents sth train service of the blocking path p, $1 \leq \bar{\alpha}_p^s \leq L$. [−]
P_l	Subset of paths that traverse along train service $l \in L$.[−]
o_l	Origin yard of train service l, $o_l \in I$.[−]
d_l	Destination yard of train service l, $d_l \in I$.[−]
τ_l^O	Schedule operation start time of the train service l at yard $o_l \in I$.[TU]
τ_l^C	Schedule cutoff time of the train service l at yard $o_l \in I$.[TU]
τ_l^D	Schedule departure time of the train service l at yard $o_l \in I$.[TU]
τ_l^A	Schedule arrival time of the train service l at yard $d_l \in I$.[TU]
U_l	Maximum number of railcars can be hauled by train service $l \in L$.[QU]
o_k	Origin yard of request k, $o_k \in I$.[−]
d_k	Destination yard of request k, $d_k \in I$.[−]
τ_k^A	Time when a request k is available at terminal o_k.[TU]
τ_k^E/τ_k^L	Early/Latest time a request k should be delivered at terminal d_k.[TU]
σ_k/ω_k	Earliness/Tardiness cost (per unit) if request k delivers earlier/later than τ_k^E/τ_k^L.[MU]
D_k	Number of railcars in request k to be shipped.[QU]
H_k	Number of hazmat railcars in request k to be shipped.[QU]
ψ_k	A charge to outsource a request k by a partner (sufficient large number).[MU]
ξ	A service level provided by the carrier, i.e., 100% means zero delay, $\xi \in [0,1]$.[−]
o_b	Origin yard of block b, $o_b \in I$.[−]
d_b	Set of possible end yards of block b, $d_b = \{i \in I \mid i \neq o_b\}$.[−]
τ_b^H	Time windows a block b is assigned to a track at the origin terminal o_b to be constructed.[TU]
θ_b	Cost to construct a block b at o_b and to perform the block-swapping process during its journey (if any).[MU]
U_b	Maximum number of cars can be assigned to block b which determined by the length of blocking track assigned to at o_b, $b \in B$.[QU]
U_i	Maximum number of blocks can be build at terminal i at any period $t \in T$ (the number of tracks), $v \in V$.[QU]
ϕ_l	Unit transportation and classification costs to ship a single commodity along direct train service $l \in L$.[MU]
q_i	Unit handling cost to transfer commodity from a train service to another at terminal i.[MU]
π_i	Free time a shipment can be stored at terminal $i \in I$ without any additional charges.[TU]
d_l	Distance along train service $l \in L$.[DU]
λ'	Set of pair of train services that can form a complete or sub path, i.e. $(l,l') \in \lambda'$ such that $d_l = o_{l'}$ *and* $\tau_l^A \leq \tau_{l'}^C$ $\forall l, l' \in L$.[−]
λ	Subset of λ' such that a train transfer occurred.[−]
$\bar{\rho_l}$	Unit inventory cost to store a commodity at yard $o_l \in I$.[MU]
ρ_l	Average population concentration along the train service l.[PU]
ζ_l	Percentage of sensitive environment area per distance along direct train service l.[$1/DU$]
$\widehat{\rho_i}$	Average population concentration at yard i.[PU]

μ_i Percentage of sensitive environment area at yard i.$[-]$

$n_l(n_i)$ Number of dangerous goods along train service l(through terminal i).

$\Theta_l(n_l)$ Threshold distance due to transport n_l dangerous goods along train service l.$[DU]$

$\Phi_i(n_i)$ Threshold zone due to transport n_i dangerous goods through terminal i.$[DU]$

$\eta_l(n_l)$ Impact area due to transport n_l dangerous goods along train service l.$[AU]$

$\chi_i(n_i)$ Impact volume due to transport n_i dangerous goods through terminal i.$[VU]$

R_l^P/R_l^E Population exposure/Environment impact threshold at train service $l \in L$ in which the service provider can reach during the planning horizon.$[PU]/[VU]$

Binary

$y_{b,p}$ =1 if block b follows path $p \in P_b$; 0 otherwise.$[-]$

$x_{k,b,l}$ =1 if request k is assigned to block b along train service l; 0 otherwise.$[-]$

z_k =1 if request k is outsourced; 0 otherwise.$[-]$

$s_{k,i}$ =1 if request k change a train at terminal i; 0 otherwise.$[-]$

Continuous

$a_{k,j}$ Arrival time of request k at yard j.$[TU]$

$h_{k,l}$ Inventory time to ship commodity k on the train service l at yard o_l, i.e., $h_{k,l} = max\{0, \tau_l^O - a_{k,j} - \pi_j\} : j \in o_l$.$[TU]$

e_k Earliness time of request k, i.e., $e_k = max\{0, \tau_k^E - a_{k,j}\} : j \in d_k$.$[TU]$

t_k Tardiness time of request k, i.e., $t_k = max\{0, a_{k,j} - \tau_k^L\} : j \in d_k$.$[TU]$

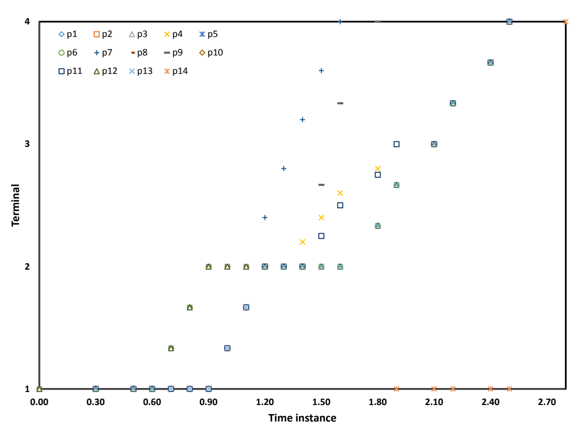


Figure A.2: Blocking paths $P_1 - P_{14}$.

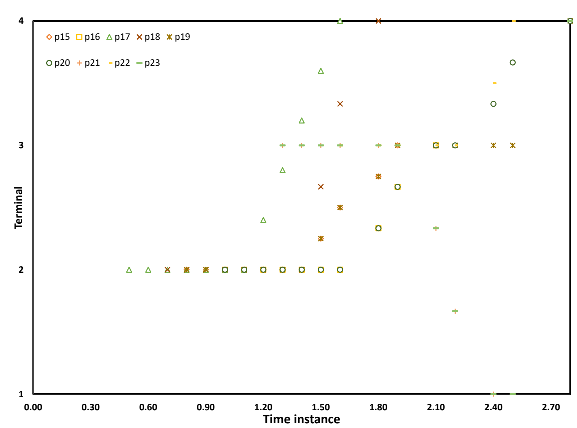


Figure A.3: Blocking paths $P_{15} - P_{23}$.

Let M be a sufficient large number, then the HTPs with blocking decisions can be modeled as follows:

$$(P') \quad min \sum_k D_k \Bigg\{ \overbrace{\overbrace{\sum_{b\in B_k}\sum_{l\in L_k\cap L_b} \phi_l x_{k,b,l}}^{\text{Shipping+sorting}} + \overbrace{\sum_{l\in L_k} \bar{\rho}_l h_{k,l}}^{\text{Holding}} + \overbrace{\sum_{i\in I} q_i s_{k,i}}^{\text{Transferring}} + \overbrace{\sigma_k e_k}^{\text{Earliness}} + \overbrace{\omega_k t_k}^{\text{Tardiness}}}^{\text{Per unit cost}} + \overbrace{\psi_k z_k}^{\text{Partner cost}} \Bigg\} + \overbrace{\sum_b \sum_{p\in P_b} \theta_{b,p} y_{b,p}}^{\text{Blocking costs}}$$

$s.t$

$$\sum_{p\in P_b} y_{b,p} \leq 1 \qquad \forall\ b : b \in B \tag{49}$$

$$\sum_{b\in B_k}\sum_{l\in L_i^+\cap L_k} x_{k,b,l} - \sum_{b\in B_k}\sum_{l\in L_i^-\cap L_k} x_{k,b,l} = \begin{cases} 1 - z_k & \forall\ k, i : i \in o_k \\ z_k - 1 & \forall\ k, i : i \in d_k \\ 0 & \forall\ k, i : i \notin o_k\ nor\ d_k \end{cases} \tag{50}$$

$$\sum_{b\in B(i,t)}\sum_{p\in P_b} y_{b,p} \leq U_i \qquad \forall i \in I, t \in \{t, .., T\} \tag{51}$$

$$\sum_k D_k x_{k,b,l} \leq \sum_{p\in P_l\cap P_b} U_b y_{b,p} \qquad \forall\ b, l : l \in L_b \tag{52}$$

$$D_k x_{k,b,l} \leq \sum_{p\in P_l\cap P_b} U_b y_{b,p} \qquad \forall\ k, b, l : l \in L_b \cap L_k \tag{53}$$

$$\sum_k \sum_{b\in B_k\cap B_l} D_k x_{k,b,l} \leq U_l \qquad \forall\ l : l \in L \tag{54}$$

$$s_{k,i} > \sum_{b\in B_k\cap B_l} x_{k,b,l} + \sum_{b\in B_k\cap B_{l'}} x_{k,b,l'} - 2 \qquad \forall\ k, l, l', i : l, l' \in L_k\ and\ (l, l') \in \lambda \tag{55}$$

$$t_k \geq max\{0, a_{k,j} - \tau_k^L\} \qquad \forall\ k, j : j \in d_k \tag{56}$$

$$e_k \geq max\{0, \tau_k^E - a_{k,j}\} \qquad \forall\ k, j : j \in d_k \tag{57}$$

$$a_{k,j} = \tau_k^A \qquad \forall\ k, j : j \in o_k \tag{58}$$

$$\Big\{\tau_l^A - a_{k,j}\Big\} \sum_{b\in B_l\cap B_k} x_{k,b,l} = 0 \qquad \forall\ k, l, j : l \in L_j^-\ and\ j \in d_l \tag{59}$$

$$\Big\{max\{0, \tau_l^O - a_{k,j} - \pi_j\} - h_{k,l}\Big\} \sum_{b\in B_l\cap B_k} x_{k,b,l} = 0\ \forall\ k, l, j : l \in L_j^+ \cap L_k\ and\ j \in o_l \tag{60}$$

$$a_{k,j} \leq \tau_l^C + M\left\{1 - \sum_{b \in B_l \cap B_k} x_{k,b,l}\right\} \quad \forall\, k, l, j : l \in L_j^+ \cap L_k \text{ and } j \in o_l \tag{61}$$

$$2\Theta_l\left(\sum_k \sum_{b \in B_l \cap B_k} H_k x_{k,b,l}\right)\rho_l q_l + \sum_{i \in I : i = d_l} \pi\Phi_i\left(\sum_k \sum_{b \in B_l \cap B_k} H_k x_{k,b,l}\right)\hat{\rho}_i \leq R_l^P \quad \forall\, l \tag{62}$$

$$\frac{1}{2}\pi\eta_l\left(\sum_k \sum_{b \in B_l \cap B_k} H_k x_{k,b,l}\right)\zeta_l q_l + \sum_{i \in I : i = d_l} \frac{2}{3}\pi\chi_i\left(\sum_k \sum_{b \in B_l \cap B_k} H_k x_{k,b,s}\right)\mu_i \leq R_l^E \;\forall\, l \tag{63}$$

$$a_{k,j}, h_{k,l}, e_k, t_k > 0 \qquad \forall\, k, j, l \tag{64}$$

$$y_{b,p}, x_{k,b,l}, z_k \in \{0, 1\} \qquad \forall\, k, b, p, l \tag{65}$$

$$1 \geq s_{k,i} \geq 0 \qquad \forall\, k, i \tag{66}$$

Objective function in the above presented model is to minimize the total costs including, respectively, the cost of shipping and classification, inventory, transfer, earliness, tardiness, and partner cost to fulfill the requests, and the cost of constructing blocks and performing block-swapping operations. Constraints (49) and (50) are commodity flow conservation constraints for set of requests being fulfilled by the carrier services, i.e., $z_k = 1$ and block, respectively. Constraints (51)-(54) are capacity limitations for yards, blocks, and total workload of services. Constraints (51) are the yard capacities for building blocks at each period. Constraints (52) link the flow of commodities with the block capacities, given that the corresponding blocks have been selected, whereas constraints (54) link flow of commodities with train with their capacities. Constraints (52) also impose that no shipment can be routed on a link unless a block routed along that link. The strong linking constraints (53) impose that no flow of any shipment can be shipped on a close block, i.e., $y_{b,p} = 0$. Although these inequalities are redundant for the MINP formulation, our experiments show that they improve the computation time. Similar inequalities have been introduced in the literature on network design problems to improve the lower bounds (i.e. Kazemzadeh et al., 2018). Constraints (55)-(60) define the set of variables. Constraints (55) impose variable $s_{k,i} = 1$ if a commodity k is assigned to a pair of compatible train services that required a train transfer at yard, i.e., $\sum_{b \in B_k \cap B_l} x_{k,b,l} + \sum_{b \in B_k \cap B_{l'}} x_{k,b,l'} = 2 | (l, l') \in \lambda$. Constraints (56) and (57) define tardiness and earliness variables, respectively. Constraints (58) and (59) define the arrival time of commodities at yards along their itineraries. In particular, constraints (58) impose the arrival time at origin terminal for demand k to τ_k^A, whereas constraints (59) define the arrival time at each terminal along its itinerary, i.e., $a_{k,i} = \tau_l^A | \sum_{b \in B_l \cap B_k} x_{k,b,l} = 1,\ and\ i = d_l$. Constraints (60) determine the holding times for demands along their itineraries, i.e., $h_{k,i} = max\{0, \tau_l^O - a_{k,j} - \pi_j\} | x_{k,b,l} = 1\ and\ i = o_l$. Constraints (61) are train connection constraints, that is any commodity cannot be hauled on a train service l until it arrives at most τ_l^C periods at terminal o_l, i.e., $a_{k,i} \leq \tau^C$. To distribute the risk in an equitable way over the population and the environment, constraints (62)/(63) impose the population exposure/risk of damage to the environment is no greater than a given threshold along that service. The first term in Constraints (62) is the sum of population exposure along the route, and the second term is that at the yard. Similarly, the first term in Constraints (63) is the sum of the damage along the route, and the second term is that at the yard. Constraints (64) and (65) are non-negativity and integrity constraints, respectively. Constraints (66) and (55) satisfy the integrity property for $s_{k,i}$ variables.

A.1 NMIP to MIP

In this section, we linearized the model to be solved by available MIP solvers. The nonlinearity of the model is caused by Constraints (59), (60), (62), and (63). Constraints (59) can be replaced by Constraints (67) and (68). Note that Constraints (67) and (68) are imposed only when a shipment is assigned to a direct train service $l \in L_j^-$ at terminal $j \in d_l$ along its itinerary, i.e., $a_{k,j} = \tau_l^A | \sum_{b \in B_l \cap B_k} x_{k,b,l} = 1, k, l \in L_j^-\ and\ j = d_l$. On the other hand, Constraints (67) and (68) are redundant if a shipment not assigned to that train service, i.e., $a_{k,j} = 0 | \sum_{b \in B_l \cap B_k} x_{k,b,l} = 0, k, l \in L_j^-\ and\ j = d_l$.

$$a_{k,j} \geq \tau_l^A + M\Big\{\sum_{b \in B_l \cap B_k} x_{k,b,l} - 1\Big\} \quad \forall\, k, l, j : l \in L_j^-\ and\ j \in d_l \tag{67}$$

$$a_{k,j} \leq \tau_l^A + M\Big\{1 - \sum_{b \in B_l \cap B_k} x_{k,b,l}\Big\} \quad \forall\, k, l, j : l \in L_j^-\ and\ j \in d_l \tag{68}$$

Constraints (69) are also introduced to replace Constraints (60). At any terminal visited by a shipment k, Constraints (69) compute the amount holding times to route the shipment along the direct train service l, i.e., $h_{k,j} = \{max\{0, \tau_l^O - a_{k,j} - \pi_j\} | x_{k,b,l} = 1, k, l \in L_j^+ \; and \; i = o_l\}$.

$$h_{k,l} \geq M\left\{\sum_{b \in B_l \cap B_k} x_{k,b,l} - 1\right\} + \tau_l^O - a_{k,j} - \pi_j \quad \forall \; k, l, j : l \in L_j^+ \; and \; j \in o_l \tag{69}$$

The nonlinear expressions in Constraints (62) and (63) to measure the risks can be linearized by a piecewise method. The technical details of the approximation function in the Gaussian Plume Model and Box Model are given in subsection 2.4.1. The resulting linear programming model, denoted as P'', can be solved by available MIP solvers.

A.2 Alternative solution method

In this section, we describe an iterative heuristic algorithm belongs to Very Large-Scaled Neighborhood Search Algorithm (VLNS) with two main subroutines of initialization (section A.2.1) and local search algorithm (section A.2.2). In the VLNS algorithms, there are two distinct methods being pursued in the literature. The first approach implicitly search large neighborhoods by solving an auxiliary optimization problem, whereas the other approach partially explore the neighborhood heuristically (Altner et al., 2014). We can find VLNS attempting to solve railway blocking problem in Ahuja et al. (2007b), Multi-resource generalized assignment problem in Yagiura et al. (2004), among others. Survey on VLNS can be found in Ahuja et al. (2007a).

A good blocking policy and train-makeup plan forms the backbone of freight transportation problem (Barnhart et al., 2000) and may also reduce the risks associated with hazmat freights. The propose heuristic starts with an initial solution and iteratively improve the current blocking plans by replacing it with its neighbor solution until the solution can no longer be improved. In our model, decisions can be grouped into design decisions $y_{b,p}$ (wherever to active or not a block between a pair of terminals of the railway network including the train services along that path) and routing decisions $x_{k,b,l}$. In our algorithm, we deal with the two types of decision in a hierarchical manner, that is, we first fix the value of design decision variables and then we solve the rail freight transportation problem using the active blocks. The algorithm has two main steps: Constructing an initial feasible solution and Re-optimizing the blocking plan.

We decompose the routing and scheduling of hazmat freights problem into two nested problems: the block-to-train assignment problem (BTA) and freight-to-block assignment problem (FBA). The first problem consists of finding the best train makeup plans given the routing of commodities. Let x^w be the FBA solution at iteration w. The formulation of block-to-train assignment model giving the trip plan decisions is the following:

$$(BTA) \qquad min \overbrace{\sum_{b} \sum_{p \in P_b} \theta_{b,p} y_{b,p}}^{\text{Blocking costs}}$$

$$s.t.$$

$$(49), (51) \tag{70}$$

$$\sum_{k} D_k x^w_{k,b,l} \leq \sum_{p \in P_l \cap P_b} U_b y_{b,p} \qquad \forall\ b, l : l \in L_b \tag{71}$$

$$D_k x^w_{k,b,l} \leq \sum_{p \in P_l \cap P_b} U_b y_{b,p} \qquad \forall\ k, b, l : l \in L_b \cap L_k \tag{72}$$

$$y_{b,p} \in \{0, 1\} \qquad \forall\ b, p : p \in P_b \tag{73}$$

The second problem obtains the optimum itineraries for the freight cars when the train-makeup plan is given. An itinerary of a commodity includes not only the direct train services it is assigned along the path, but also the blocking-path it traverses along the route. Let y^w be the BTA solution at iteration w. Given a fixed train makeup on the services at iteration w, y^w, the formulation of the freight-to-block assignment model is the following:

$$(FBA) \quad min \sum_{k} D_k \Big\{ \overbrace{\sum_{b} \sum_{l \in L_k \cap L_b} \phi_l x_{k,b,l} + \sum_{l \in L_k} \bar{\rho}_l h_{k,l} + \sum_{i \in I} q_i s_{k,i} + \sigma_k e_k + \omega_k t_k}^{\text{Serving costs}} + \overbrace{\psi_k z_k}^{\text{Partner cost}} \Big\}$$

$$s.t.$$

$$(50), (54) - (64), (66)$$

$$\sum_{k} D_k x_{k,b,l} \leq \sum_{p \in P_l \cap P_b} U_b y^w_{b,p} \qquad \forall\ b, l : l \in L_b \tag{74}$$

$$D_k x_{k,b,l} \leq \sum_{p \in P_l \cap P_b} U_b y^w_{b,p} \qquad \forall\ k, b, l : l \in L_b \cap L_k \tag{75}$$

$$x_{k,b,l}, z_k \in \{0, 1\} \qquad \forall\ k, b, l, i \tag{76}$$

To solve FBA, we design an algorithm that solve the rail freight transportation problem given the blocking plans and order of requests with their characteristics. The set of itineraries for each shipment is given by the set of paths on restricted graph defined through $y_{b,p}$ variables. At an iteration w, the algorithm finds the cheapest itinerary for a given number of freight cars, D_k, for request k. In generating the trip plan, we imposed the capacity constraints (52) and (54) at services and yards as well as the risk thresholds in Constraints (62)-(63). Briefly, the main steps of the algorithm are the following:

Step 1 Select a request $k^* \in K$ still not assign to an itinerary. If none exists: STOP. Let x^w be the FBA solution at iteration w;

Step 2 Determine the cheapest itinerary considering the capacities of blocks and trains and risk thresholds by extension of the k-shortest path algorithm;

Step 3 Step 3.0 If at least one itinerary exists: Go 3.1 otherwise Go to 3.4
Step 3.1 Assign the request to that itinerary, $x^w_{k,b^*,l^*} = 1\ \forall b^*, l^*$ along the cheapest itinerary, where (b^*, l^*) is a block segment along the cheapest itinerary.
Step 3.2 Compute Δf^w_k, where Δf^w_k denotes the change in the objective value incurred by assigning shipment k to the cheapest itinerary at iteration w.
Step 3.3 Update the capacity on the blocks and yards as well as the risk thresholds along that itinerary.
Step 3.4 If no itinerary exist, then foreword the request to a partner to fulfill the demand, i.e., $z_k = 1$ and compute Δf^w_k. Go to Step 1 if $k < |K|$; Otherwise stops;

A.2.1 Constructing an initial feasible solution

We design a constructive algorithm to find an initial solution by solving BTA then the restricted FBA is solved. The following procedures produce a complete train and freight plans. First, we assign the blocks in B, one by one following their order in the list, to the best blocking paths in $p \in P_b$ that maximize the number of blocking sections with respect to the yard limitations. Next, we update train and terminal capacities along blocking path after assigning a block to one of its feasible blocking paths. The process continues until all candidate blocks are assigned to a train path or it is not possible to insert additional block in a solution. After we solve the BTA, we assign each shipment to the cheapest itinerary (if exist). The algorithm performs at most K iterations as it serves one shipment at a time in each iteration. If there no feasible itineraries for a shipment, we set $f_k^w = \psi_k$. This process continues until all shipments have been served or no more shipments can be inserted in the solution. At the end of this phase, an initial solution is stored as the best (x^B, y^B) solution obtained so far. The objective function then calculated and the best objective function Z^B is updated.

We also developed several other routines to find an initial solution. However, our computational results indicate that the algorithm can explore the solution space extensively regardless the quality of initial solution.

A.2.2 Local search

Problem P is a generalized assignment which involves two main related assignment decisions: the assignment of blocks to train paths, through $y_{b,p}$ variables, and the assignment of freights to itineraries, through $x_{k,b,l}$ variables, according to the selected blocking plans. The method focuses on the $y_{b,p}$ binary variables, as they specified the highest level assignment decision, so mainly influence the dimension of the solution space. In our approach, we optimize a block at a time until additional improvement is not possible, while fixing the other blocking plans in a solution. The heuristic iteratively performs a predefined number of local search procedures. In each local search, we destroy a blocking path, one at a time, and replace it by one of its neighbor (if exist). Then we calculate the change in the objective value on the freight routing. Once all blocking paths have been considered, the blocking paths that are destroyed are considered, again in increasing order of blocking path, and the best path while the other blocking paths fixed is found. We adopt a simulated annealing approach to avoid local optima. A formal statement of the solution method is provided below.

Initi.: Set $w=0$, $z^C=\infty$, $z^B=\infty$, where z^C and z^B denote the current and best objective value, respectively. Let m_b^w (f_k^w) be the cost of block b (shipment k) to be constructed (served) at iteration w;

Step 1: *Construct an initial solution for P':*

Step 1.a: Solve BTA: for each potential block b in B determine the best blocking path that maximize the number of segments to be constructed: $p^* \leftarrow \text{argmax}_{p\in P_b}\{|\bar{\sigma_p}| : Constraints(51)\ are\ satisfied\}$. If at least one blocking path exists, then assign the block to that path, $y_{b,p^*}=1$, update the current objective by adding the cost of construction block and performing the block-swapping operations (if any), $z^C \leftarrow z^C + m_b^w$, and Update the blocking limitation along that path p^*. Otherwise set $y_{b,p}=0$. Go to Step 1.a if $b < |B|$ Otherwise Go to Step 1.b;

Step 1.b: Solve FTB on the restricted graph defined by $y_{b,p}$ variables: Determine the cheapest itinerary considering the capacities of blocks and trains, and the risk thresholds by calling an extension of shortest path algorithm. Go to step 2;

Step 2: Update the current objective: $z^C \leftarrow z^C + \sum_k f_k^w$. Update the best solution found: if $z^C < z^B$ then $z^B = z^C$.

Step 3: *Local search*:
for each *pass* in bypass and b in B:
set $w \leftarrow w+1$:

Step 3.1: If b is constructed, destroy the block, i.e., $y_{b,p^*}^w=0|y_{b,p^*}^{w-1}=1$. Update the blocking limitations along train sequence p^*. Go to Step 3.1;

Step 3.2: for each p in P_b, where $p \neq p^*$:
Assign b to p if Constraints (51) are satisfied. If $y_{b,p}^w=1$ Calculate $\Delta m_b^w = \theta_{b,p} - \theta_{b,p^*}$ and then Go to step 3.3. Otherwise Go to Step 3.2 if $p < |P_b|$;

Step 3.3: Resolve FTB on the new restricted graph and then update $z^C \leftarrow z^C + \sum_b \Delta m_b^w + \sum_k \Delta f_k^w$. Calculate the objective difference $\Delta = z(x^C, y^C) - z(x^B, y^B)$. Then, (x^C, y^C) replaces (x^B, y^B) whenever $\Delta < 0$. Otherwise, x^C could be accepted with a probability $p((x^C, y^C), (x^B, y^B)) = e^{-\Delta/T}$. The acceptance probability is compared to a number $r \in [0,1]$ is generated randomly and (x^C, y^C) is accepted if and only if $p((x^C, y^C), (x^B, y^B)) > r$. Terminate and return the best solution found so far if number of bypass reached and $b=|B|$. Otherwise Go to Step 3;

Appendix B

Case study

The proposed solution method is also applied to a sub-network of Class-I railroad derived from Canadian Pacific (CP) Railway, given in Figure B.1. CP's network has numerous routing alternative across Canada and the U.S. and further extended its network with other major Class I railways in North America. The study uses two groups of data: network and commodity flow data. The network characteristics include mileages between terminals, tracks between major cities and list of train services.

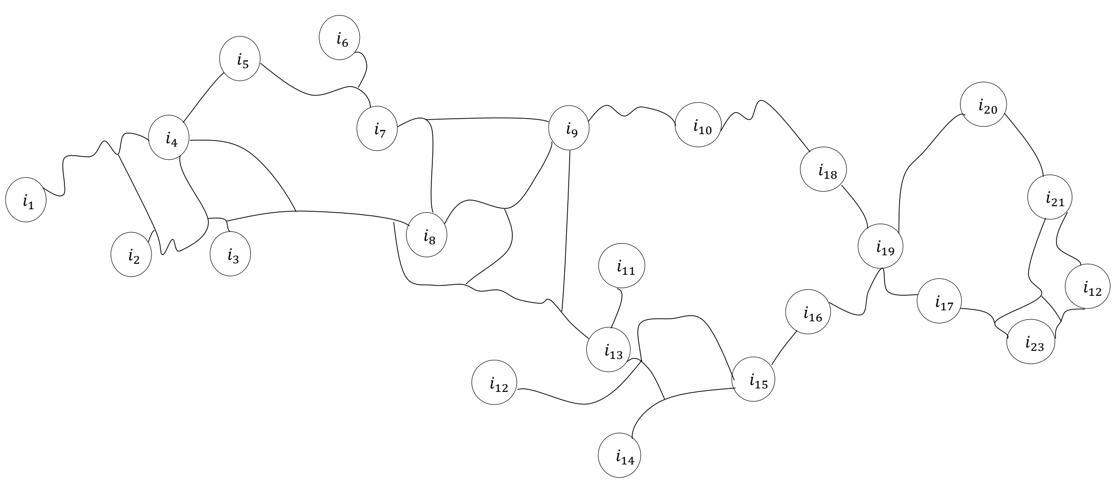


Figure B.1: Sub-network of Canadian Pacific (CP) railway.

The sub-network consists of 23 terminals and 63 links. We create 60 (hypothetical) train services that consists of 1-3 train legs, a total of 147 service legs were created connecting

Table B.1: Network data for CP railroad network.

Terminal	*Notation*	*Number of trains Dep.(Arr.)*
Vancouver	i_1	10(6)
Kingsgate	i_2	10(8)
Coutts	i_3	8(9)
Calgary	i_4	19(19)
Edmonton	i_5	3(3)
Lloydminster	i_6	2(2)
Saskatoon	i_7	7(5)
Regina	i_8	11(16)
Winnipeg	i_9	13(17)
ThunderBay	i_{10}	2(2)
Duluh	i_{11}	1(1)
Tracy	i_{12}	4(4)
Minneapolis/ST.Paul	i_{13}	15(15)
Kanas City	i_{14}	4(3)
Chicago	i_{15}	6(7)
Detroit	i_{16}	3(3)
Buffalo	i_{17}	6(6)
Sudbury	i_{18}	2(2)
Toronto	i_{19}	4(4)
Montreal	i_{20}	2(2)
Albany	i_{21}	6(5)
New York	i_{22}	4(3)
Philadelphia	i_{23}	4(6)

any two of the 23 yards in the network. Table B.1 gives the name and number of train services departure from/terminate at each terminal. The available network data which aided the process were obtained from the CP railroad's website. Freight flow data were generated randomly with a total of 288 origin-destination pairs. Given the network data, the number of available paths for each original-destination pair ranges from 1 to 67, and the total number of itineraries for all 288 origin-destination pairs is 5380.

We introduced two indicators, called *shortest distance indicators*, to measure the percent deviation from shortest distance, the first indicator called *Average Distance Gap* ($\overline{ADG}$) and the second quantity called *Shortest Distance Gap* ($\overline{SDG}$), that we computed after solving the problem. For each request k, we compute $\underline{d_k}$ and $\overline{d_k}$ as the shortest and average distance for serving request k, respectively. Let $\overline{ADG}$ be the average deviation of the actual distance travel from average distance of the available itineraries for the commodity, obtained from:

$$\overline{ADG} = \frac{\sum_k ADG_k}{\sum_k (1 - z_k)} \times 100 = \frac{\sum_k \left\{ \sum_b \sum_l d_l x_{k,b,l} - \overline{d_k} \right\}}{\sum_k \overline{d_k} (\sum_k (1 - z_k))} \times 100$$

The denominator in $\overline{ADG}$ is the difference between the actual distance travel by the commodities from the average distance of the available itineraries for the requests. The average distance of the available itineraries $\overline{d_k}$ is a priori computed as the ratio between the sum of distance travel by each of the possible itineraries and the total number of itineraries for request k. Let Q_k be the set of possible itineraries for request k, indexed by q. Also, let $\eta_{q,l}$ be indicator equal to 1 if direct train service $l \in L$ belongs to itinerary $q \in Q_k$ and otherwise 0. Then, the average distance of the available itineraries for shipment k is calculated from:

$$\overline{d_k} = \frac{\sum_q \sum_l \eta_{q,l} d_l}{|Q_k|}$$

Given the network and commodity flow data, Table B.2 and Table B.3 gives the total number of possible itineraries to transport a shipment from terminal $i \in o_k$ to terminal $j \in d_k$ and the average distance travel by shipment k, respectively.

The $\overline{SDG}$ is an estimate of the average deviation from the shortest distance which defined as:

$$\overline{SDG} = \frac{\sum_k \{\sum_l \sum_b d_l x_{k,b,l} - \operatorname{argmin}_{q \in Q_k} \{\sum_l d_l \eta_{q,l}\}\}}{\sum_k \operatorname{argmin}_{q \in Q_k} \{\sum_l d_l \eta_{q,l}\} (\sum_k (1 - z_k))} \times 100$$

The denominator in $\overline{SDG}$ is the sum of deviations from the shortest distances of the considered requests, whereas the numerator calculates the average sum of the shortest distances. Note that the higher values of these two indicators mean the additional operational costs that carrier incurred due to imposing risks threshold and/or capacities constraints.

We conducted various experiments characterized by different parameters of the problem to create a comprehensive image of freight movement among major cities. We generated six groups of instances, two for the demand rate, two for the train capacity, two for block capacity, two for population threshold, two for environment impact and two for terminal

Table B.2: Number of itineraries from terminal i to j.

From/To	i_1	i_2	i_3	i_4	i_5	i_6	i_7	i_8	i_9	i_{10}	i_{11}	i_{12}	i_{13}	i_{14}	i_{15}	i_{16}	i_{17}	i_{18}	i_{19}	i_{20}	i_{21}	i_{22}	i_{23}
i_1	-	14	23	25	16	21	62	12	20	10	24	59	37	61	25	10	10	10	10	10	20	10	20
i_2	38	-	18	37	21	26	82	17	28	14	30	80	50	85	39	14	14	14	14	14	28	14	28
i_3	30	20	-	20	19	22	79	13	23	14	34	88	47	93	39	14	14	14	14	14	28	14	28
i_4	42	18	19	-	1	25	55	13	24	15	26	69	43	75	38	15	15	15	15	15	30	15	30
i_5	18	10	15	4	-	11	26	6	11	6	14	36	20	38	16	6	6	6	6	6	12	6	12
i_6	18	10	15	4	2	-	24	6	11	6	13	36	18	37	16	6	6	6	6	6	12	6	12
i_7	37	24	32	37	17	2	-	9	26	13	25	67	40	74	37	13	13	13	13	13	26	13	26
i_8	9	7	10	15	7	6	19	-	5	3	6	16	10	18	9	3	3	3	3	3	6	3	6
i_9	10	8	10	13	5	3	12	5	-	1	4	11	6	12	5	1	1	1	1	1	2	1	2
i_{10}	1	1	2	3	1	1	4	1	1	-	2	5	4	5	2	1	1	1	1	1	2	1	2
i_{11}	16	11	16	25	10	12	25	4	10	3	-	8	1	9	5	3	4	3	3	7	12	7	10
i_{12}	14	9	13	24	10	10	24	2	8	2	4	-	7	6	5	2	3	2	2	6	10	6	8
i_{13}	16	11	16	25	11	12	24	4	10	3	1	9	-	10	5	3	3	3	3	7	13	5	10
i_{14}	14	9	13	24	10	10	24	2	8	2	4	6	5	-	5	2	3	2	2	6	10	6	8
i_{15}	14	5	13	24	10	10	21	2	8	2	3	4	5	5	-	1	3	2	2	6	10	6	8
i_{16}	1	1	2	3	1	1	4	1	1	1	2	5	4	5	2	-	2	1	1	5	8	5	6
i_{17}	1	1	2	3	1	1	4	1	1	1	2	5	7	5	3	2	-	1	1	3	5	3	4
i_{18}	1	1	2	3	1	1	4	1	1	1	2	5	4	5	2	1	1	-	1	1	2	1	2
i_{19}	1	1	2	3	1	1	4	1	1	1	2	5	4	5	2	1	1	1	-	2	3	2	3
i_{20}	1	1	2	3	1	1	4	1	1	1	2	5	4	5	2	1	1	1	1	-	3	2	3
i_{21}	2	2	3	7	2	2	8	2	2	2	4	10	14	9	6	4	4	2	2	3	-	4	7
i_{22}	1	1	2	3	1	1	4	1	1	1	2	5	7	5	3	2	4	1	1	6	12	-	7
i_{23}	1	1	2	3	1	1	4	1	1	1	2	5	7	5	3	2	2	1	1	3	5	4	-

capacity. Table B.4 gives various values of the parameters used in our experiments. Table B.5 shows the computational results of the proposed solution method for each scenario. Note that the linearized MIP model of P_1 model cannot be solved for large scale instances. The first column (with Table B.4) gives information of the instance and second column presents the objective function of the proposed algorithm. The next two columns give the unit population exposure and environment impact per hazmat freight for all planned services. In particular, unit population exposure and environment impact are obtained from the following expressions:

$$Pop.\,risk = \sum_l \left(2\Theta_l\left(\sum_k \sum_b H_k x_{k,b,l}\right)\rho_l q_l + \sum_{i\in I} \pi\Phi_i\left(\sum_k \sum_b H_k x_{k,b,l}\right)\hat{\rho}_i\right) \Big/ \sum_k H_k(1-z_k)$$

$$Env.\,impact = \sum_l \left(\frac{1}{2}\pi\eta_l\left(\sum_k \sum_b H_k x_{k,b,l}\right)\zeta_l q_l + \sum_{i\in I} \frac{2}{3}\pi\chi_i\left(\sum_k \sum_b H_k x_{k,b,s}\right)\mu_i\right) \Big/ \sum_k H_k(1-z_k)$$

Column 5 and 6 gives the value of $\overline{ADG}$ and $\overline{SDG}$ indicators, respectively. Note that negative value for $\overline{ADG}$ indicates that the total actual kilometers covered by commodities

Table B.3: Average distance between terminals (in kilometers).

From/To	i_1	i_2	i_3	i_4	i_5	i_6	i_7	i_8	i_9	i_10	i_{11}	i_{12}	i_{13}	i_{14}	i_{15}	i_{16}	i_{17}	i_{18}	i_{19}	i_{20}	i_{21}	i_{22}	i_{23}
i_1	-	4108	4861	4377	4839	4918	6084	3849	3930	4584	5796	6380	6870	6936	5754	6273	6039	5382	5804	6907	6685	6321	6509
i_2	4703	-	3602	4947	4404	4213	5279	3086	3314	3927	4658	5304	5852	5848	4963	5616	5382	4725	5147	6250	6027	5664	5851
i_3	4468	3406	-	4090	4030	3886	5224	2722	2851	3596	4708	5213	5415	5729	4613	5285	5051	4394	4816	5919	5696	5333	5520
i_4	4640	3075	3025	-	329	3988	4931	2770	2946	3751	4354	4976	5644	5476	4753	5440	5206	4549	4971	6074	5852	5488	5676
i_5	4268	2999	3536	3232	-	3521	4749	2269	2701	3215	4389	4873	5052	5406	4309	4904	4670	4013	4435	5538	5316	4952	5140
i_6	4643	3337	3845	3021	1725	-	4957	2550	3046	3497	4459	5178	5285	5633	4626	5186	4952	4295	4717	5820	5597	5234	5421
i_7	4241	3473	3708	4144	3499	587	-	2075	3027	3224	3847	4536	4866	5042	4344	4913	4679	4022	4444	5547	5325	4961	5149
i_8	3303	2642	3088	3723	2816	2519	3516	-	1596	2026	2852	3530	3945	4033	3329	3715	3481	2824	3246	4349	4127	3763	3951
i_9	3414	2672	2962	3175	2239	2151	3276	1854	-	751	2834	3714	3461	4216	3079	2440	2206	1549	1971	3074	2852	2488	2676
i_{10}	3660	3003	3543	3590	2839	1901	3549	1736	774	-	2476	3083	3338	3707	2265	1689	1455	798	1220	2323	2101	1737	1925
i_{11}	4306	3539	4158	4566	3583	4301	4125	3719	3473	3340	-	3279	94	3611	2971	3903	3391	3606	3747	3755	3665	3410	3612
i_{12}	4466	3561	4012	4970	3895	4390	4329	3273	3578	2558	2446	-	2383	2514	1943	2558	2456	2558	2558	3285	3095	2980	2889
i_{13}	4212	3445	4064	4472	3398	4207	3878	3625	3379	3246	235	3775	-	3999	2877	3809	3810	3512	3653	3661	3500	3872	3518
i_{14}	5571	4641	5065	6041	4982	5477	5373	4106	4649	3391	3280	4380	2619	-	2469	3391	3184	3391	3391	3907	3739	3603	3565
i_{15}	4807	3886	4231	5231	4193	4688	4429	2980	3839	2265	2018	1877	2055	2515	-	4247	1917	2265	2265	2499	2359	2195	2227
i16	5349	4692	5232	5279	4528	3590	4394	3425	2463	1689	2476	3421	2493	4045	2265	-	587	891	469	1741	1502	1492	1193
i17	5115	4458	4998	5045	4294	3356	4336	3191	2229	1455	2594	3468	2833	4092	1917	587	-	657	235	1095	1000	1072	792
i18	4458	3801	4341	4388	3637	2699	3948	2534	1572	798	2476	3243	2939	3867	2265	891	657	-	422	1525	1303	939	1127
i_{19}	4880	4223	4763	4810	4059	3121	4159	2956	1994	1220	2476	3327	2728	3951	2265	469	235	422	-	845	939	916	900
i_{20}	5467	4810	5350	5397	4646	3708	4746	3543	2581	1807	3063	3914	3315	4538	2852	1056	822	1009	587	-	1135	916	1096
i_{21}	5749	5092	5507	5793	4928	3990	4970	3825	2863	2089	3228	4102	3467	4467	2551	1221	869	1291	869	1127	-	652	818
i_{22}	5702	5045	5585	5632	4881	3943	4923	3778	2816	2042	3181	4055	3420	4679	2504	1174	957	1244	822	1572	1176	-	748
i_{23}	5819	5162	5702	5749	4998	4060	5040	3895	2933	2159	3298	4172	3537	4796	2621	1291	669	1361	939	1533	1028	1209	-

is less than the average distance of the available itineraries. Column 7 gives the average train utilization, whereas column 8 presents the average block utilization. These indicators are obtained from the following expressions:

$$Avg.\ Train\ utilization = \frac{\sum\limits_{l}\left(\sum\limits_{k}\sum\limits_{b\in B_l\cap B_k} D_k x_{k,b,l} \Big/ U_l\right)}{|L|} \times 100$$

$$Avg.\ Block\ utilization = \frac{\sum\limits_{b}\sum\limits_{l\in L_b}\left(\sum\limits_{k}\sum\limits_{p\in P_l\cap P_b} D_k x_{k,b,l} y_{b,p} \Big/ U_b\right)}{\sum\limits_{b}\sum\limits_{l\in L_b}\sum\limits_{p\in P_b\cap P_l} y_{b,p}} \times 100$$

The last two columns display the total number of freights (including hamzat) being served and total number of freights to be reclassified, respectively.

Table B.4: Parameters of the case study.

Scenario/Para.	*Demand rate*	*Train capacity*	*Block capacity*	*Pop. threshold*	*Env. threshold*	*Terminal capacity*
Default	$U(5,8)/U(2,5)$	$U(80,220)$	$U(50,60)$	60000	7000	6
$S1$	$U(2,5)/U(3,6)$	$U(80,220)$	$U(50,60)$	60000	7000	6
$S2$	$U(6,10)/U(1,3)$	$U(80,220)$	$U(50,60)$	60000	7000	6
$S3$	$U(5,8)/U(2,5)$	$U(80,150)$	$U(50,60)$	60000	7000	6
$S4$	$U(5,8)/U(2,5)$	$U(120,320)$	$U(50,60)$	60000	7000	6
$S5$	$U(5,8)/U(2,5)$	$U(80,220)$	$U(40,50)$	60000	7000	6
$S6$	$U(5,8)/U(2,5)$	$U(80,220)$	$U(60,90)$	60000	7000	6
$S7$	$U(5,8)/U(2,5)$	$U(80,220)$	$U(50,60)$	40000	7000	6
$S8$	$U(5,8)/U(2,5)$	$U(80,220)$	$U(50,60)$	100000	7000	6
$S9$	$U(5,8)/U(2,5)$	$U(80,220)$	$U(50,60)$	60000	4000	6
$S10$	$U(5,8)/U(2,5)$	$U(80,220)$	$U(50,60)$	60000	6500	6
$S11$	$U(5,8)/U(2,5)$	$U(80,220)$	$U(50,60)$	60000	7000	4
$S12$	$U(5,8)/U(2,5)$	$U(80,220)$	$U(50,60)$	60000	7000	8

One may notice decreases in the number of freights being served, by an average of 12.4%, when the number of hazmat freights increases per request ($S2$). The reason of this decreases could be explained by analyzing the value of the shortest distance indicator. As we expect, the average shortest distance gap increased by 11.24% as most of the commodities followed longer paths to avoid some risky train services. This decrease in the number of shipments served also shows the benefits of using the partner services in reducing the risks associated with hazmat transportation. As the number of hazmat freights increases, the algorithm transfers the hazmat risk to the transport network of the partner as the population exposure and/or environment damages exceed the given thresholds. Of course, we assume the transport risk incurred on the partner network is less what would be exposed on the railroad network, i.e., pipelines or marine. Also, one may observe increases in the population exposure and environment impact per unit, on average by 5.07% and 5.25%, respectively. Such increases could be explained by the fact that many requests with high number hazmat freights follow longer itineraries, with an average deviation from shortest distance of 21.55% (compared to the one in $S2$), to satisfy either the population exposure and environment impact thresholds or capacities limitations. In contrast, when the proportion of regular freights is higher than hazmat freights in request ($S2$), the shortest distance gap decreases by an average of 10.81%.

Train capacity is another factor that has remarkable impact on the routing and scheduling of the hamzat freights. We generated two instances of the considered problem by varying the train capacity: one with compact train services ($S3$) and another with loose train services ($S4$). Among all instances we conducted, we noticed that train capacity has the most significant increases on the shortest distance indicators and risks per unit as capacity decreases. In fact, increasing train capacities would increase the dimension of solution space. Hence, more routing options to schedule the active blocks when the capacity of train increases. Therefore, the chance to obtain a high quality solution is relatively high in the case of loose train services. For instance, the average shortest distance gap decreases by -30.64% when the capacity of the trains increases. Increasing the capacities of train services with atmospheric class E or F could decrease the additional operational costs from serving hazmat freights. In contrary, the block capacity ($S5$ and $S6$) has less influence on the shortest distance indicators and risks per unit compare to train capacity.

We also studied the effect of risk thresholds by changing the given population exposure ($S7$ and $S8$) and environment damages ($S9$ and $S10$) thresholds. In contrast to population exposure threshold, we observed the total cost decreases when the environment impact threshold increases. The reason behind this observation could be explained by the fact that as the environment impact threshold increases, more routing and scheduling alternatives are available for the considered requests.

Table B.5: Computational results for CP network.

Scenario/ Perf.	*Obj.*	*Pop. risk*	*Env. impact*	*Avg. distance gap*	*Min. distance gap*	*Avg. Train utilization*	*Avg. Block utilization*	$\sum_k D_k(\sum_k H_k)$	*Total Sorting*
Default	764800	724.60	60.16	−35.90	19.34	49.94	51.23	2958(1020)	961
$S1$	729200	762.65	63.21	−34.48	21.55	45.24	43.91	2590(1466)	919
$S2$	773800	712.51	56.50	−36.80	17.25	52.91	49.66	2982(568)	1129
$S3$	708500	690.90	55.57	−35.83	20.27	56.20	44.84	2771(955)	942
$S4$	929100	759.60	58.24	−38.54	13.41	41.59	58.47	3380(1170)	1359
$S5$	770200	716.83	60.32	−37.86	15.81	49.48	57.12	2937(1012)	1078
$S6$	761700	716.42	56.60	−36.27	19.13	52.26	37.69	2958(1021)	968
$S7$	758400	704.82	58.81	−37.24	16.13	50.08	49.72	2958(1021)	962
$S8$	773700	743.22	63.98	−36.21	19.32	50.31	48.02	2963(1014)	1058
$S9$	780000	681.02	50.72	−36.59	17.48	48.65	48.76	2953(1015)	1087
$S10$	754500	730.94	63.33	−36.43	18.62	49.63	49.60	2955(1020)	961
$S11$	801400	704.80	56.23	−34.06	24.64	50.47	48.97	2955(1021)	1114
$S12$	712900	761.67	71.05	−36.31	20.63	51.80	38.45	2805(962)	887

The last two scenarios investigate the number of blocking track at each railway terminal of the considered study. One may note the total cost decreases when the number of tracks at the terminal increase by an average of -6.79% as the number of tracks change to 8. The reason behind this situation could be that the additional design costs to build more blocks (toward less risky train services) is less than the increase in operation costs of rerouting the demands.

In the last part of this section, we analyzed the criticality of the CP network links by determining the set services that commodities compete over the remaining capacity. At each scenario conducted in Table B.5, we listed the train service legs that have been utilized more than 90% of the train service. As expected (i_{15}, i_{13}); (i_{15}, i_{16}); (i_{18}, i_{19}); (i_{19}, i_{18}); (i_7, i_9); (i_9, i_{10}) railway links are among the top critical links on CP's network. The reasons for such observation are the unbalance of supply and demand and the network design of the CP's sub-network. Given that fact that the supply and demand locations are always different, the flow of demands between Western and Eastern Canada as well as the U.S. are unbalanced. In addition, those railway links connect western Canada with the U.S. and Eastern Canada. The railway manager must pay attention by increasing the safety requirements on those links to enhance the overall safety of the railway network.

Appendix C

Modeling and solution method for HTPTD

The HTPTD determines the train and freight transportation plan such as the track capacities, train capacities, and risk thresholds constraints are satisfied. For each train service $t \in \mathcal{T}$, the operator selects one of its possible timetable such as the track capacity constraints are satisfied and the overtaking between train services happens only within terminals. Such restrictions ensure that train services never occupy simultaneously incompatible tracks. Furthermore, for each terminal in the network, there is a minimum time interval between two consecutive departures (arrivals). The last restrictions prevent congestion at terminals and guarantee connection with trains on different services for some demands. The train service could be canceled if it is economically to do so. For each of request k in K_1, it will be assigned to a sequence of train services, referred to as itinerary, to minimize the total costs for serving the requests while satisfying train capacities and risk thresholds constraints. Details of two rail planning problems are given below:

Train timetabling problem: We consider $|\mathcal{T}|$ train services to be scheduled, their route, en-route stops, and capacity are defined in advance, and are not decisions to be made. Let $\mathcal{T} = \{t_1, .., t_{|\mathcal{T}|}\}$ be the set of candidate train services. It was assumed that there is a fixed number of train departures between any terminals in the network. For simplicity, train departure times are discretized (i.e. Caprara et al., 2002; Gorman, 1998), and expressed as integers from 1 to 42, each four hours in a week. One may use a finer discretization, for example, each 1/2 hour or less, without modifying the proposed model, however the time and space complexity of the algorithm will increase considerably. Let S be the set of train departure times. For each train departure $s \in S$, let o_s be the origin yard, d_s the destination yard, and τ_s^o,τ_s^c,τ_s^d, and τ_s^a be the the operation start time, cutoff time, schedule departure, and schedule arrival of train departure s, respectively. For each train service $t \in \mathcal{T}$, it was assumed the first terminal f_t, the final terminal l_t, and the sequence of direct train services traverses by train t are given. A timetable specifies, for each train service t, the departure time from first terminal f_t, the arrival at final terminal l_t, and the waiting times at the intermediate terminals along its journey.

Rail freight transportation problem: A railway operator, a central decision maker, is in charge to manage customer requests, denoted by $k \in K_1$, for a carload moves within a railway network in addition to the train timetabling problem. In response to these planned train services, the operator receives a set of requests for carload moves hereafter called requests. For each request k in K_1, the operator is given the pickup o_k and delivery yard d_k, and the earliest available time τ_k^{AL}. It was also assumed that the operator has sufficient capacity to serve all the traditional requests. For each request k in K_1, it will be assigned to a sequence of train services, referred to as itinerary, by the operator.

For modeling purpose, the following sets, parameters, decision variables, and auxiliary variables are introduced:

Sets

J	Set of railway terminals, index by $j \in J$.
K_1	Set of traditional demands, index by $k \in K_1$.
S	Set of train departures in time and space, index by $s \in S$.
P_t	Collection of possible timetables for train t, index by $p \in P_t$.
P	Overall (multi-)collection of the timetables for all candidate trains, index by $p \in P$.
P_s	Subcollection of paths that uses train departure s, index by $p \in P_s$.
I_k	Collection of possible itineraries for request k, index by $v \in I_k$.
I	Overall (multi-)collection of itineraries for the consider requests, index by $v \in I$.
I_l	Subcollection of itineraries that travel along train service l, index by $v \in I_l$.

Parameters

o_k	Origin yard of request k, $o_k \in J$.
d_k	Destination yard of request k, $d_k \in J$.
o_s	Origin yard of train departure s, $o_s \in J$.
d_s	Destination yard of train departure s, $d_s \in J$.
$a(b)$	Minimum time interval between two consecutive departures (arrivals).
D_k	Quantity of regular freights in request k, $k \in K_1$.
H_k	Quantity of hazmat freights in request k, $k \in K_1$.
τ_k^{AL}	Available time for request k, $k \in K_1$.
U_l^{INI}	Initial capacity of train service l, $l \in L$.
R_l^{INI}	Initial population exposure threshold along train service l, $l \in L$.
τ_s^o	Schedule operation start time of the train departure s at yard $o_s \in J$, $s \in S$.
τ_s^c	Schedule cutoff time of the train departure s at yard $o_s \in J$, $s \in S$.
τ_s^d	Schedule departure time of the train departure s at yard $o_s \in J$, $s \in S$.
τ_s^a	Schedule arrival time of the train departure s at yard $d_s \in J$, $s \in S$.
ζ_l	Percent of train capacities that is booked for irregular demands along train service l, $l \in L$.
$1-\theta_l$	Percent of risk thresholds that is being on hold to accommodate irregular demands (hazmat) along train service l, $l \in L$.
$\Delta(s,s')$	Time difference between the schedule departure of train departure s' from s, $\Delta(s,s') = \tau_{s'}^d - \tau_s^d$, $s, s' \in S$.
c_v^T	Cost to transport a request along itinerary v, $v \in I$.
$c_{l,l'}^H$	Cost to hold a demand at $d_l(o_{l'})$ yard per time $l, l' \in L$.
c^H	Average cost to hold a demand at yard per unit time.
$c_{t,p}^D$	Cost to assign train t to path p, i.e, locomotive requirements and waiting times costs, $t \in \mathcal{T}$, $p \in P_t$.
$\psi_{p,s}$	Indicator = 1 if train path p uses sth train departure; 0 otherwise.
$\omega_{v,l}$	Indicator = 1 if itinerary v uses train leg l; 0 otherwise.
n_p	Number of train departures on path p, $1 \leq r \leq n_p$.
n_t	Number of train legs (segment) on train t, $1 \leq r \leq n_t$.
$\bar{n}_v$	Number of train legs (segment) on itinerary v, $1 \leq r \leq \bar{n}_v$.
$\alpha_{s,r,p}$	Indicator =1 if train departure s is the rth departure on train path p; 0 otherwise, $1 \leq r \leq n_p$.
$\bar{\alpha}_{l,r,v}$	Indicator =1 if train leg l is the rth train leg on itinerary v; 0 otherwise, $1 \leq r \leq \bar{n}_v$.
$\lambda'_{l,r,t}$	Indicator =1 if train leg l is the rth train leg on train t; 0 otherwise, $1 \leq r \leq n_t$.

Variables

Integer

$y_{t,p}$	=1 if train t is assigned to path (or timetable) p; 0 otherwise.
$x_{k,v}$	=1 if demand k follows itinerary v; 0 otherwise.
w_v	=1 if itinerary v is available; 0 otherwise.
$u_{l,l'}$	=1 if the train sequences l' scheduled after train service l; 0 otherwise, i.e., $u_{l,l'} = 1$ if $\tau_{l'}^c \geq \tau_l^a$.

Continuous

τ_l^o	Actual schedule operation start time of the direct train service l.

τ_l^c	Actual schedule cutoff time of the direct train service l.
τ_l^d	Actual schedule departure time of the direct train service l.
τ_l^a	Actual schedule arrival time of the direct train service l.
$h_{l,l'}$	Holding time to shipped a demand along the pair of services l and l', i.e., $h_{l,l'} = max\{0, \tau_{l'}^o - \tau_l^a\}$.
I_v	Holding times to shipped a demand along itinerary v.

Then the HTPTD formulation can be stated as follows:

$$(P_6) \quad Min \quad Z_4 = \overbrace{\sum_{t\in\mathcal{T}}\sum_{p\in P_t} c_{t,p}^D x_{t,p} + \sum_{l\in L}\sum_{\substack{l':l\neq l'\\ d_l=o_{l'}}} c_{l,l'}^H h_{l,l'}}^{\text{Train costs}} + \overbrace{\sum_{k\in K_1} D_k \sum_{v\in I_k}[c_v^T + c^H I_v]x_{k,v}}^{\text{Serving costs}}$$

$s.t.$

$$\sum_{t\in\mathcal{T}}\sum_{p\in P_t} y_{t,p} \leq 1 \qquad \forall t : t\in\mathcal{T} \tag{77}$$

$$h_{l,l'} \geq \tau_{l'}^o - \tau_l^a \qquad \forall l, l' : o_{l'} = d_l \tag{78}$$

$$\sum_{\substack{s':\tau_{s'}^d\geq\tau_s^d\\ \Delta(s,s')<min(a,b)}} \sum_{t\in\mathcal{T}}\sum_{p\in P_t\cap P_{s'}} y_{t,p} \leq 1 \qquad \forall s : s\in S \tag{79}$$

$$\tau_l^o = \sum_{p\in P_t}\sum_{s:\alpha_{s,r,p}=1} \tau_s^o y_{t,p} \qquad \forall t, r, l : \lambda_{l,r,t}^{'} = 1 \tag{80}$$

$$\tau_l^c = \sum_{p\in P_t}\sum_{s:\alpha_{s,r,p}=1} \tau_s^c y_{t,p} \qquad \forall t, r, l : \lambda_{l,r,t}^{'} = 1 \tag{81}$$

$$\tau_l^d = \sum_{p\in P_t}\sum_{s:\alpha_{s,r,p}=1} \tau_s^d y_{t,p} \qquad \forall t, r, l : \lambda_{l,r,t}^{'} = 1 \tag{82}$$

$$\tau_l^a = \sum_{p\in P_t}\sum_{s:\alpha_{s,r,p}=1} \tau_s^a y_{t,p} \qquad \forall t, r, l : \lambda_{l,r,t}^{'} = 1 \tag{83}$$

$$\sum_{v\in I_k} x_{k,v} = 1 \qquad \forall k : k\in K_1 \tag{84}$$

$$\sum_{k\in K_1}\sum_{v\in I_k\cap I_l} D_k x_{k,v} \leq \sum_{p\in P_t}(1-\zeta_l)U_l^{INI} y_{t,p} \qquad \forall t, r, l : \lambda_{l,r,t}^{'} = 1 \tag{85}$$

$$\tau_k^{AL} x_{k,v} \leq \tau_l^c \qquad \forall k, v, l, r : v\in I_v, \bar{\alpha}_{l,r,v} = 1, r = 1 \tag{86}$$

$$\sum_{k\in K_1} x_{k,v} \leq |K_1| w_v \qquad \forall v : v\in I \tag{87}$$

$$w_v \leq \sum_{r=1}^{\bar{n}_v - 1} \sum_{l:\bar{\alpha}_{l,r,v}=1} \sum_{\substack{l':l\neq l'\\ \bar{\alpha}_{l',r+1,v}=1}} u_{l,l'} - \bar{n}_v + 1 \qquad \forall v : v\in I \tag{88}$$

$$\tau_{l'}^c - \tau_l^a + M(1-u_{l,l'}) \geq 0 \qquad \forall l, l' : l\neq l', d_l = o_{l'} \tag{89}$$

$$I_v \geq \sum_{r=1}^{\bar{n}_v-1} \sum_{l:\bar{\alpha}_{l,r,v}=1} \sum_{\substack{l':l\neq l' \\ \bar{\alpha}_{l',r+1,v}=1}} h_{l,l'} \qquad \forall v: v \in I \tag{90}$$

$$2\Theta_l\Big(\sum_{k\in K_1}\sum_{v\in I_k\cap I_l} H_k x_{k,v}\Big)\rho_l q_l + \pi\Phi_j\Big(\sum_{k\in K_1}\sum_{v\in I_k\cap I_l} H_k x_{k,v}\Big)\hat{\rho}_j \leq \theta_l R_l^{INI} \;\forall l, j: j = d_l \tag{91}$$

$$h_{l,l'} \geq 0 \;\; \forall l, l' \in L, l \neq l', d_l = o'_l; I_v \geq 0 \;\; \forall v \in I, \tau_l^o, \tau_l^c, \tau_l^d, \tau_l^a \geq 0 \quad \forall l \in L \tag{92}$$

$$x_{k,v} \in \{0,1\} \quad \forall k \in K_1, v \in I; y_{t,p} \in \{0,1\} \forall t \in \mathcal{T}, p \in P_t \tag{93}$$

$$w_v \in \{0,1\} \quad \forall v \in I; h_{l,l'} \in \{0,1\}; u_{l,l'} \in \{0,1\} \qquad \forall l, l' \in L, l \neq l', d_l = o'_l \tag{94}$$

Objective function Z_4 in the above model P_6 is to minimize the train design cost and the cost from serving the railway requests. The first two terms in Z_4 aims at minimizing trains design cost and the cost of waiting between different services at terminals. The third and fourth terms minimize the cost of transporting and holding cost for serving the commodities. Constraints (77) guarantee a single path (or timetable) is assigned for each train service. Constraints (78) define the waiting times between consecutive train services. Constraints (79) prevent two consecutive arrivals and departures of train services at terminals to be too close for safety reasons. Constraints (80)-(83) define the actual operation start times, cutoff times, schedule departure, and schedule arrival for train services, respectively. Constraints (84) commodity flow conservation constraints. Constraints (85) link the flow of commodities with the train capacity for the candidate trains. Constraints (86) ensure that requests arrive not later than the cutoff time of the train services along routes, whereas constraints (87) identify the available itinerary considering the travel times along the itinerary. Constraints (88)-(89) state that the itinerary cannot be used if any of its pair of train services along that itinerary is not available. Constraints (90) compute the amount of inventory times along the itinerary. Constraints (91) limit the risk associated with hazmat freights into the given thresholds. Note that, the operator reserves some spaces on train services and holds a percentage of the population risk thresholds to accommodate some irregular requests. Constraints (92)-(94) are non-negativity and integrity requirements.

Problem P_6 is a version of Capacitated Multicommodity Network Design (CMND) problem, which is known to be NP-hard (Magnanti and Wong, 1984; Minoux, 1989). In fact, problem P_6 can be decomposed into two subproblems, train timetabling problem (TTP) and freight transportation problem (FTP) by relaxing Constraints (85). Caprara et al. (2002) prove the TTP is NP-hard. The latter problem is a version of the Multicommodity Minimum Cost Network Flow Problem (MCNFP). Although the special versions of the MCNFP can be efficiently solved in polynomial time, some generalizations of the MCNFP are intractable. An integer flow for the minimum cost multicommodity flow such as when routing nonbifurcated units of traffic is computationally difficult. Even et al. (1976a) proved that the unsplittable version of MCNFP is NP-complete. Furthermore, the flow over time MCNFP is known to be NP-hard (Cai et al., 2001).

The routing and scheduling of hazmat freights problem was decomposed into two nested subproblems: the TTP and FTP. The first problem consists of finding the best timetables of the trains given the itineraries of demands. Let X^w be the TTP solutions at iteration w. The formulation of TTP model giving the trip plan decisions (P_7) is the following:

$$(P_7) \qquad Min \qquad Z_5 = \overbrace{\sum_{t\in\mathcal{T}}\sum_{p\in P_t} c^D_{t,p}x_{t,p} + \sum_{l\in L}\sum_{\substack{l':l\neq l'\\ d_l=o_{l'}}} c^H_{l,l'}h_{l,l'}}^{\text{Trains costs}}$$

$s.t.$

$$(77)-(83);\,(89)$$

$$\sum_{k\in K_1}\sum_{v\in I_k\cap I_l} D_k x^w_{k,v} \leq \sum_{p\in P_t}(1-\zeta_l)U^{INI}_l y_{t,p} \qquad \forall t,r,l:\lambda^{'}_{l,r,t}=1 \tag{95}$$

$$w^w_v \leq \sum_{r=1}^{\bar{n}_v-1}\sum_{l:\bar{\alpha}_{l,r,v}=1}\sum_{\substack{l':l\neq l'\\ \bar{\alpha}_{l',r+1,v}=1}} u_{l,l'} - \bar{n}_v + 1 \qquad \forall v: v\in I \tag{96}$$

$$\tau^o_l,\tau^c_l,\tau^d_l,\tau^a_l \geq 0 \quad \forall l: l\in L \tag{97}$$

$$y_{t,p}\in\{0,1\} \quad \forall t,p: t\in\mathcal{T}, p\in P_t; \tag{98}$$

$$u_{l,l'}\in\{0,1\} \quad \forall l,l': l,l'\in L, l\neq l', d_l=o'_l \tag{99}$$

The second problem is to obtain the optimum itineraries for the freight cars when the schedules of the trains are given. An itinerary of a commodity includes not only the direct train services it is assigned along the path, but also the blocking path it traverses along the route. Given the solution of the TTP:

- Let Y^w be the timetables of the trains t at iteration w;
- Let U^w be the trains sequences at iteration w;
- Let H^w be the waiting times between train services at iteration w

Then, the formulation of the rail freight transportation problem, P_8, is the following:

$$(P_8) \qquad Min \qquad Z_6 = \overbrace{\sum_{k \in K_1} D_k \Big[\sum_{v \in I_k} [c_v^T + c^H I_v] x_{k,v} \Big]}^{\text{Serving costs}}$$

$s.t.$

$$\sum_{v \in I_k} x_{k,v} = 1 \qquad \forall k : k \in K_1 \tag{100}$$

$$\sum_{k \in K_1} \sum_{v \in I_k \cap I_l} D_k x_{k,v} \leq \sum_{p \in P_t} (1 - \zeta_l) U_l^{INI} y_{t,p}^w \qquad \forall t, r, l : \lambda'_{l,r,t} = 1 \tag{101}$$

$$\tau_k^{AL} x_{k,v} \leq \tau_l^{c^*} \qquad \forall k, v, l, r : \bar{\alpha}_{l,r,v} = 1, r = 1 \tag{102}$$

$$\sum_{k \in K_1} x_{k,v} \leq |K_1| w_v \qquad \forall v : v \in I \tag{103}$$

$$w_v \leq \sum_{r=1}^{\bar{n}_v - 1} \sum_{l : \bar{\alpha}_{l,r,v} = 1} \sum_{\substack{l' : l \neq l' \\ \bar{\alpha}_{l',r+1,v} = 1}} u_{l,l'}^* - \bar{n}_v + 1 \qquad \forall v : v \in I \tag{104}$$

$$I_v \geq \sum_{r=1}^{\bar{n}_v - 1} \sum_{l : \bar{\alpha}_{l,r,v} = 1} \sum_{\substack{l' : l \neq l' \\ \bar{\alpha}_{l',r+1,v} = 1}} h_{l,l'}^* \qquad \forall v : v \in I \tag{105}$$

$$2\Theta_l \Big(\sum_{k \in K_1} \sum_{v \in I_k \cap I_l} H_k x_{k,v} \Big) \rho_l q_l + \pi \Phi_j \Big(\sum_{k \in K_1} \sum_{v \in I_k \cap I_l} H_k x_{k,v} \Big) \hat{\rho}_j \leq \theta_l R_l^{INI} \ \forall l, j : j = d_l \tag{106}$$

$$I_v \geq 0 \quad \forall v \tag{107}$$

$$w_v \in \{0, 1\} \quad \forall v \in I; x_{k,v} \in \{0, 1\} \quad \forall k \in K_1, v \in I \tag{108}$$

We designed heuristic method to solve the HTTP. One may also design one of available (meta)heuristic in the literature (Caprara et al., 2002,0; Gorman, 1998; Huntley et al., 1995;

Kwon et al., 1998; Lulli et al., 2011; Marin and Salmeron, 1996), with specific modifications to the considered problem.

Appendix D

Main steps of the two-phase heuristic

Figure D.1: Two-phase heuristic.