2017

Intermodal Network Design and Expansion for Freight Transportation

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INTERMODAL NETWORK DESIGN AND EXPANSION FOR FREIGHT TRANSPORTATION

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Submitted in Partial Fulfillment of the Requirements

For the Degree of Doctor of Philosophy in

Civil Engineering

College of Engineering and Computing

University of South Carolina

2017

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DEDICATION

This dissertation is dedicated to my life companion, Hamed, my beautiful daughter, Bahar and to my parents, Mostafa and Ferdous, who have helped me a lot through my successes.

ACKNOWLEDGEMENTS

I would like to sincerely thank my advisor, Dr. Nathan Huynh. Dr. Huynh is certainly a tremendous mentor for me. I would like to thank him for supporting my research and encouraging me to grow as a researcher. His advice, both on research and my career have been priceless. I was fortunate to have Drs. Robert Mullen, Juan Caicedo and Pelin Pekgun as my PhD committee members.

ABSTRACT

Over the last 50 years, international trade has grown considerably, and this growth has strained the global supply chains and their underlying support infrastructures. Consequently, shippers and receivers have to look for more efficient ways to transport their goods. In recent years, intermodal transport is becoming an increasingly attractive alternative to shippers, and this trend is likely to continue as governmental agencies are considering policies to induce a freight modal shift from road to intermodal to alleviate highway congestion and emissions. Intermodal freight transport involves using more than one mode, and thus, it is a more complex transport process. The factors that affect the overall efficiency of intermodal transport include, but not limited to: 1) cost of each mode, 2) trip time of each mode, 3) transfer time to another mode, and 4) location of that transfer (intermodal terminal). One of the reasons for the inefficiencies in intermodal freight transportation is the lack of planning on where to locate intermodal facilities in the transportation network and which infrastructure to expand to accommodate growth. This dissertation focuses on the intermodal network design problem and it extends previous works in three aspects: 1) address competition among intermodal service providers, 2) incorporate uncertainty of demand and supply in the design, and 3) incorporate multi-period planning into investment decisions. The following provides an overview of the works that have been completed in this dissertation.

This work formulated robust optimization models for the problem of finding near-optimal locations for new intermodal terminals and their capacities for a railroad company, which operates an intermodal network in a competitive environment with uncertain demands. To solve the robust models, a Simulated Annealing (SA) algorithm was developed. Experimental results indicated that the SA solutions (i.e. objective function values) are comparable to those obtained using GAMS, but the SA algorithm can obtain solutions faster and can solve much larger problems. Also, the results verified that solutions obtained from the robust models are more effective in dealing with uncertain demand scenarios.

In a second study, a robust Mixed-Integer Linear Program (MILP) was developed to assist railroad operators with intermodal network expansion decisions. Specifically, the objective of the model was to identify critical rail links to retrofit, locations to establish new terminals, and existing terminals to expand, where the intermodal freight network is subject to demand and supply uncertainties. Addition considerations by the model included a finite overall budget for investment, limited capacities on network links and at intermodal terminals, and due dates for shipments. A hybrid genetic algorithm was developed to solve the proposed MILP. It utilized a column generation algorithm for freight flow assignment and a shortest path labeling algorithm for routing decisions. Experimental results indicated that the developed algorithm can produce optimal solutions efficiently for both small-sized and large-sized intermodal freight networks. The results also verified that the developed model outperformed the traditional network design model with no uncertainty in terms of total network cost.

The last study investigated the impact of multi-period approach in intermodal network expansion and routing decisions. A multi-period network design model was proposed to find when and where to locate new terminals, expand existing terminals and retrofit weaker links of the network over an extended planning period. Unlike the traditional static model, the planning horizon was divided into multiple periods in the multi-period model with different time scales for routing and design decisions. Expansion decisions were subject to budget constraints, demand uncertainty and network disruptions. A hybrid Simulated Annealing algorithm was developed to solve this NP-hard model. Model and algorithm's application were investigated with two numerical case studies. The results verified the superiority of the multi-period model versus the single-period one in terms of total transportation cost and capacity utilization.

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CHAPTER 1: INTRODUCTION

An efficient transportation strategy with the minimum social and environmental costs is very important due to the increasing need of freight transport and concerns for the global warming. Intermodal transportation is the transportation of goods in the same loading unit with successive modes of transport and without handling the goods while transferring them between modes at intermodal terminals. It has the advantage of accessibility of road, load capacity of rail, speed of air and economies of scale of barge. Containers are highly standard loading units extensively used for intermodal freight transportation. Although the use of more than one mode in intermodal transportation can reduce the carbon foot print and total transportation costs, the road transportation dominates the other modes/combination of modes for transporting goods over short and/or medium distances. A significant portion of intermodal transportation costs is from transfer of loads at terminals. Although the transportation cost per ton/mile is less for the intermodal option, it cannot compensate the transfer cost while moving cargo over short and/or medium distances. Hence, it becomes an option for moving the freights over the long distances.

In early ages of intermodal logistics, the most freight belonged to domestic sector which did not entail the long distances. Therefore, intermodal transportation was not as common as road transportation with shorter average travel times. However, the market globalization raised the need of intermodal transportation as an alternative shipping option for moving the freights over the long distances, i.e. between the countries and continents. The huge amount of global freights also generated the domestic demands. This increased the need for intermodal transportation in the countries with expanded lands, such as U.S. The success of an intermodal network mainly depends on comprehensive collaboration of its different modes due to their inherent differences in terms of cost, capacity, emission and accessibility. The low level of maturity of intermodal transportation stems from poor selection of terminal locations and connectivity of modes. Intermodal logistic providers need to realign their existing networks to reach the maximum costs reduction, connectivity and efficiency.

The primary objective of this research is to address multiple real-world criteria in intermodal network design and expansion decisions, which compared to traditionally designed projects, can provide cost savings for intermodal service providers. Three mathematical models are developed and the appropriate meta-heuristic algorithms are proposed to solve these models. These models are, 1) competitive intermodal network expansion with uncertain demands, 2) reliable intermodal network expansion with demand uncertainties and network disruptions, and 3) reliable multi-period intermodal network expansion problem. These models are concerned with location optimization, freight flow assignment and shared common objectives, such as minimizing the total cost (which may include transportation, establishment and loss costs of unmet demand) or maximizing the provider's market share.

1.1 RESEARCH TOPIC 1- INTERMODAL NETWORK EXPANSION IN A COMPETITIVE ENVIRONMENT WITH UNCERTAIN DEMANDS

The location of terminals is important for success of an intermodal transportation system since the terminals transfer costs and times are the main portions of total transportation cost and time of intermodal shipments. If a railroad company intends to build the new terminals, it is important to consider the competitors offering the same service in overlapping service areas. That company should not lose the business of its existing terminals by building the new ones either. The first study of this dissertation addresses the intermodal network expansion problem, including the networks competition. A robust model is proposed to consider the uncertainty of future demand. Since this model is NP-hard (non-deterministic polynomial-time hard), a Simulated Annealing (SA) approach is proposed to solve it for large size instances. The experimental results verify that this algorithm can find optimal results faster than a well-known optimization solver (GAMS). Readers are referred to chapter 3 of this dissertation for a comprehensive problem description. A review of related background is also discussed along with the developed methodologies to formulate and solve this problem in order to implement them for the related case studies.

1.2 RESEARCH TOPIC 2- RELIABLE INTERMODAL FREIGHT NETWORK EXPANSION WITH DEMAND UNCERTAINITIES AND NETWORK DISRUPTIONS

An intermodal network is composed of links and terminals. Despite the critical effect of terminals on the network efficiency, the expansion or maintenance of terminals connecting links are very important as each network reliability stems from reliability of both links and nodes. The second part of this dissertation studies the possible investment decisions for an intermodal network expansion. This includes the expansion of existing terminals and retrofit of higher-risk links in addition to building the new terminals. Natural or human-made disasters occur in every infrastructure. Thus, a robust mathematical model is proposed to include such future disruptions in network elements as well as uncertain future demands. A hybrid Genetic Algorithm (GA) embedded with an intermodal label setting algorithm is proposed to solve this NP-hard model. The experimental results of small size case studies verify that it is faster than an Exhaustive Enumeration (EE) method to find the optimal solutions (EE cannot find any solutions for medium and large size problems either). The model and GA applications are also discussed for a large size case study. The results confirm that this model can reduce the total network cost of an intermodal service provider by considering the parameter uncertainties for investment decisions. Chapter 4 of this dissertation presents the details of this problem, its related background and proposed model with its algorithm. It also discusses the relevant results as well.

1.3 RESEARCH TOPIC 3- A RELIABLE MULTI-PERIOD INTERMODAL FREIGHT NETWORK EXPANSION PROBLEM

Network expansion is typically a long term and time-consuming project requiring a high investment budget. In the classical network expansion problems, all the decisions are made at the beginning of the planning horizon within a short time. However, in a practical situation, the companies start with a small network configuration and utilize the revenue gained from goods transportation for capital investment needed for further network expansions. This mitigates the financial burden on the company for such a comprehensive project as well as better network design due to changes in locations and amount of demand over the planning horizon. The third work of this dissertation develops a model that dynamically locates new intermodal terminals, expands existing intermodal terminals and retrofits weaker links in an intermodal transportation network over several time periods with limited budgets. It is assumed that network capacity might be reduced due to the disruptions that might happen during expansion intervals. A shorter time scale is considered for routing decisions in order to control the uncertainties of the network under expansion intervals. The objective is minimization of total transportation and establishment costs over all time periods. A hybrid SA algorithm embedded with a heuristic for freight flow assignment is proposed to solve this model. The chapter 5 of this dissertation gives a comprehensive overview of the proposed model and algorithm as well as their applications in different networks.

1.4 LIST OF PAPERS AND STRUCTURE OF DISSERTATION

This dissertation is written following a manuscript format. Chapter 2 provides a brief overview of intermodal network and highlights related studies. Chapters 3, 4 and 5 are the works of the following research articles published and submitted in peer-reviewed journals.

1. Fotuhi, F., Huynh, N. (2015) Intermodal network expansion in a competitive environment with uncertain demands. *International Journal of Industrial Engineering Computations*, 6 (2): 285-304.
2. Fotuhi, F., Huynh, N. (2016) Reliable Intermodal Freight Network Expansion with Demand Uncertainties and Network Disruptions. *Networks and Spatial Economics*, 1-29.
3. Fotuhi, F., Huynh, N. A Reliable Multi-Period Intermodal Network Expansion Problem. Submitted to *Journal of Computers and Industrial Engineering*. March 2017.

Chapter 6 provides the concluding remarks of this dissertation.

CHAPTER 2: BACKGROUND AND LITERATURE REVIEW

This chapter presents an overview of intermodal network components and operations with a review of related studies as well as the contribution of this dissertation to this field.

2.1 INTERMODAL FREIGHT TRANSPORTATION

Intermodal freight transportation involves at least two modes of transport. Figure 2.1 illustrates a simple depiction of intermodal network that consists of shipping origins and destinations, a highway network that connects all origins and all destinations, limited number of intermodal terminals, and rail, air or barge networks that connect the various intermodal terminals. Freight can be directly shipped only through the highway mode or first shipped to a nearby intermodal terminal with truck, then to another intermodal terminal near the destination through another mode, such as rail, air or barge, and finally delivered to the destination with truck. Drayage is the trucking part of this trip while the transport among intermodal terminals is called long-haul. The optimal shipment method depends on the distance between origin and destination, proximity of intermodal terminals to them, type of available intermodal terminal (i.e. rail, air or barge), and transportation and transfer costs. This dissertation considers road and rail as the only operation modes of an intermodal network.

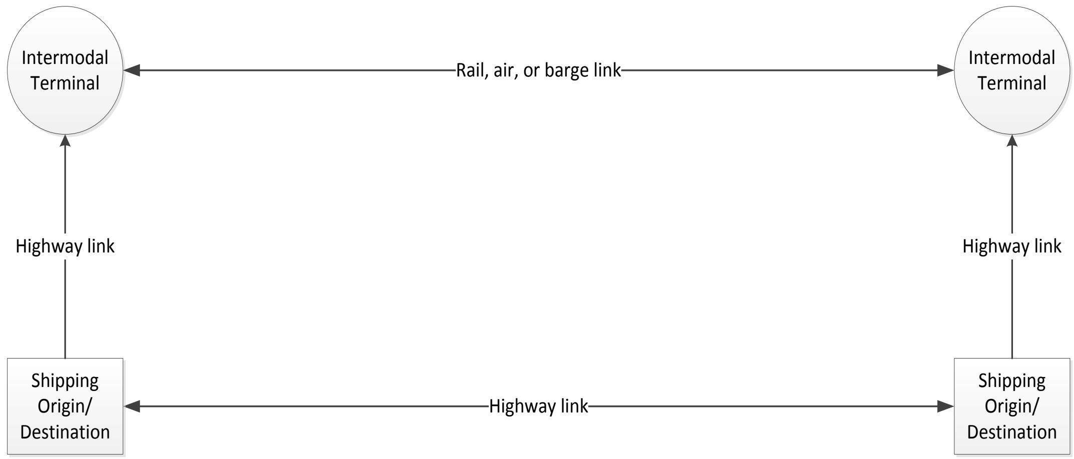


Figure 2.1. Illustration of an intermodal freight network.

Intermodal transportation is an interesting business option due to its low costs, such as transportation, environmental and social costs. In a consolidation system, the low volume cargos are moved to consolidation centers and bundled into the larger packages. Then, rail, air and/or barge transport the shipments between intermodal terminals as high-frequency and capacity transport modes with lower cost per load (discounted cost). Consolidation centers are known as hubs. In traditional hub-and-spoke networks, each pair of origins and destinations could use at most two hubs with no direct shipment between them. Although intermodal transportation can be considered as a hub-based system, the various network topologies other than hub-and-spoke can represent it (Figure 2.2). The type of commodity is important for choosing the type of appropriate intermodal topology (SteadieSeifi et al., 2014) especially for multi-commodity shipping businesses. Intermodal option is not an option for some commodities, such as perishable items and live animals, due to long travel times. Thus, a direct shipment option is needed where trucks move these specific cargo that the hub-and-spoke networks with no direct option cannot work for. This research focuses more on connected hubs and dynamic routes topology of intermodal network design problems. However, the related studies about hub network design are addressed in this dissertation due to similarities of intermodal and network design problems.

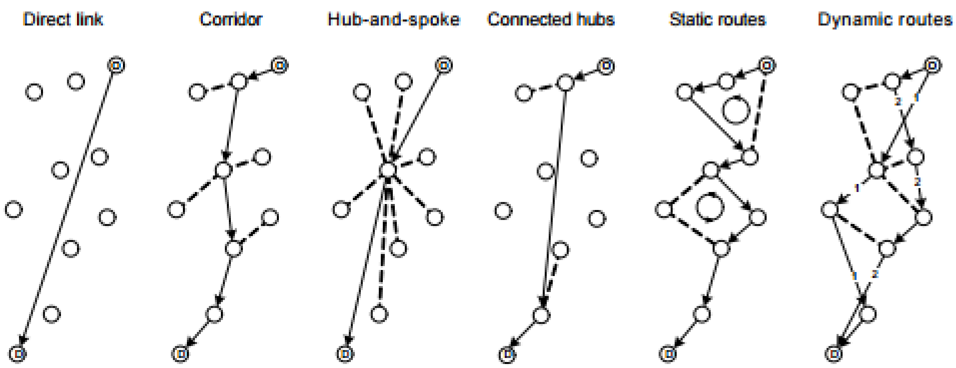


Figure 2.2. Six options to move cargo between an OD pair (Woxenius, 2007).

The intermodal transportation involves multiple operators, such as drayage, terminal, network and intermodal operators (Macharis and Bontekoning 2004). Drayage operators schedule and plan the truck operations between terminals, shippers and/or receivers. The terminal operators control the transfers between modes of a terminal. Network operators are responsible for infrastructure planning and operations while the intermodal operators select the route to move the freight in network.

Intermodal network design involves strategic, tactical and operational planning levels (SteadieSeifi et al. 2014). Strategic planning relates with investment decisions for infrastructure establishment. It requires huge capital investment and a long implementation time. It is also difficult to change the strategic plans once a network is configured. Terminal layout design and construction of terminal and links are a few of these decisions. Tactical planning uses the given infrastructure over the month or week time scales. For example, choosing transportation modes, scheduling their trips and frequencies, and allocation of their capacities to shipments are some of these decisions. Operational planning is about the day-to-day decisions for a network. Like tactical level, the goal is finding the itineraries and best allocation of shipments for an existing infrastructure. However, it is more flexible for real time changes in network elements and operators which can be due to availability of terminal or link, labor or driver, and train or truck. Accidents, weather changes, equipment failure, labor strikes and employee sick days can cause routing plans changes. This dissertation is mainly focused on strategic and tactical decisions however an operational decision is studied in one of its models.

Arnold et al. (2001) proposed one of the very first intermodal network design models. Their Mixed Integer Linear Programming (MILP) model found the optimal locations of intermodal terminals and routed the freight over a network by minimizing the total establishment and routing costs. Each demand has one set of origin and destination (shipper and receiver) with truck and intermodal shipping options. Later in 2004, they proposed an alternative model that considered intermodal terminals as network edges. This led to a huge reduction in number of decision variables. Racunica and Wynter (2005) developed a model to find the optimal locations of intermodal terminals in a rail/road network as well as train frequencies over it. They also showed how much market a terminal can capture from road-only option if added to the network. Groothedde et al. (2005) proposed an initial model for road/inland-barge intermodal network. The barge was selected as an alternative mode due to its economies of scale. They compared their model with a road-only option for a case study in Netherland. The results revealed that barge is more suitable for the stable part of the trip and the road is more beneficial where dealing with variations in the demand over a short period of time. Limbourg and Jourquin (2009) proposed a p-hub median model for intermodal terminal location problem. Their model optimally locates *p* intermodal terminals over the network by minimizing the total transportation cost. They used the demand density to choose potential locations of intermodal terminals in a European intermodal network. All the aforementioned studies intended to minimize the system costs.

Intermodal transportation outperforms the road option in terms of total transportation cost but it has longer travel time due to dwell time of terminals. Dwell time is the waiting time of a container at a terminal while being transferred between modes. Based on a recent study in US, the dwell time at a terminal is 24 hours by average (ITIC document). Ishfaq and Sox (2010) added a time window constraint to their intermodal network design model to prevent intermodal routes with long travel times. Each demand should arrive at its destination no later than a predefined time window. Moreover, they considered more than two modes in their model. Despite terminal locations decision and freight assignment, their model chose which mode should operate in each terminal. A piecewise linear cost function was considered for long-haul truck shipments as it decreases over the miles traveled. The objective was to minimize total fixed cost of building terminals, transportation and modal connectivity costs at terminals. Later, they formulated a hub location-allocation model for intermodal network design ignoring the truck-only option (Ishfaq and Sox 2011).

Limited storage for containers and labor at terminals can cause limited capacity at intermodal terminals in real life applications. By relaxing this constraint, the closest terminal is always selected for each OD pair. Incorporating this important feature in intermodal network design models can significantly change freight allocation to the network. Sorensen et al. (2012) improved Ishfaq and Sox (2011) model by adding the capacity constraint at terminals. They also let shipments select truck-only option to avoid lost demand due to limited capacity at intermodal routes. However, they did not incorporate time window constraint in their model. Due to limited capacity, different fractions of a specific order can use different routes. Lin et al. (2014) proposed an alternative model for Sorensen et al. (2012) ones by reducing a huge set of decision variables. They showed that the new model can find optimal solutions for larger size instances compared to the Sorensen ones.

2.2 COMPETITION BETWEEN INTERMODAL SERVICE PROVIDERS

Most studies in intermodal network design assumed a central entity managing an unified network of multiple intermodal service providers from different countries (Case of European network). However, a different common case exists for network of regional or large countries with extended lands (like US). Private railroad companies with decentralized management offer intermodal services in this case. Although their initial network had serviced different areas, their service areas started to overlap as their networks and business were expanding. Figure 2.3 depicts a map of intermodal networks for five class 1 railroad companies in US and one covering Canada. Norfolk Southern Rail Road (NSRR), and CSX move freight within the East Coast and South East of US. Burlington Northern Santa Fe (BNSF) and Union Pacific Rail Road (UPRR) covers the rest of US. Canadian Pacific Rail Road (CPRR) starts from North part of US and goes all the way to Canada. Lastly, Canadian National Rail Road (CNRR) serves eastern Canada. It is evident that these companies have overlapping service areas and they compete to attract more demand to their own terminals in those areas to increase their market shares.

This example shows two real-world criteria which have not received enough attention in previous studies of intermodal network design. First, most companies have existing terminals operating in a network. Their main concern is how to expand their network by locating the new intermodal terminals in order to survive in such a competitive market rather than building a network from scratch (Gelareh et al. 2010). Second, the private companies compete to attract more demand to their intermodal networks, specially those having overlapping service areas. This criterion does not exist in networks operated by a central entity.

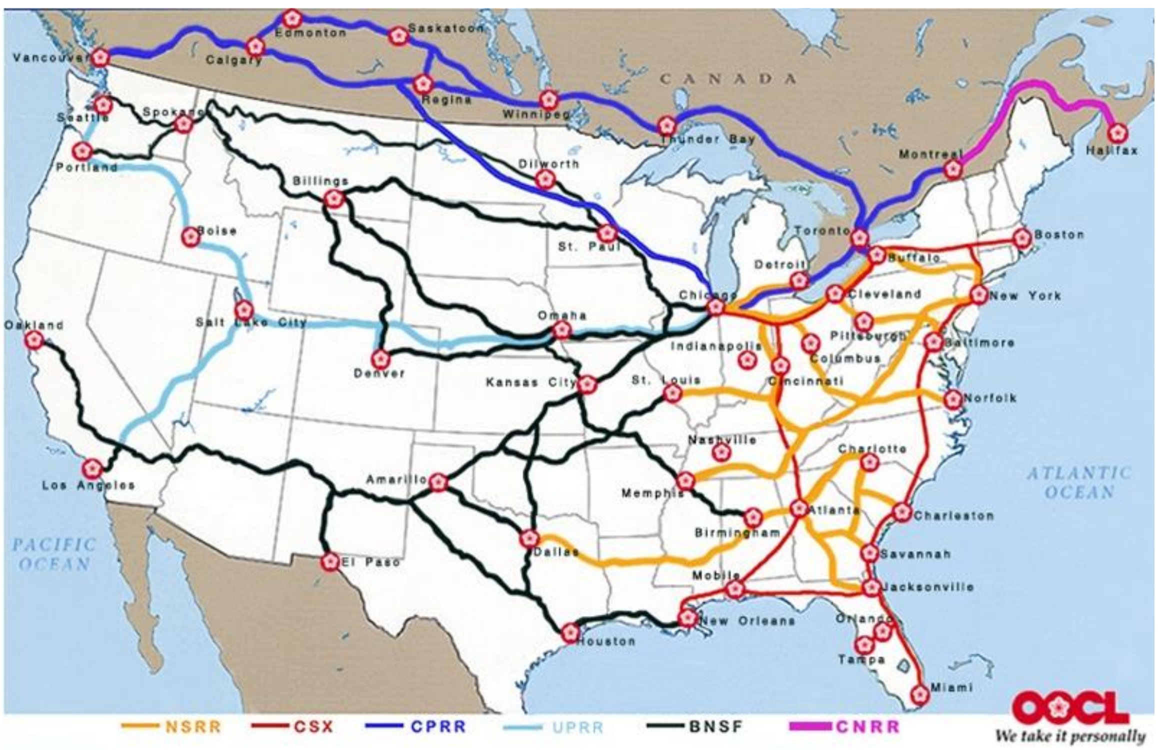


Figure 1.3 North America rail road companies intermodal network map (http://www.oocl.com)

Although a remarkable number of papers studied competition for facility location problems, less work have been done for hub-type location problems. In 1999, Marianov et al. presented the first model for competitive hub location problem. A new coming company decided to build its network in an overlapping area with another company offering the same service. The demand for each OD pair was captured by the new coming company if its transportation cost was less than the competing company's one. The objective of this model was to come up with optimal locations for hubs to maximize the market captured by the new company. Gelareh et al. (2010) developed a model for competitive liner shipping hub network design. They assumed a new liner shipping provider comes to a market and competes with an existing liner shipping company in terms of transportation cost and service time. The new company intended to locate *p* new ports in the network to capture the demand from the existing company and attract new demands to its network. The objective was to minimize total cost and transportation time for the new service provider.

In an early work, Huff (1964) studied the attraction of different markets for customers. He developed a methodology (Huff's gravity model) showing that attraction of an area has a direct connection with attractiveness of that area (i.e. Size and variety of stores in a shopping mall) and is inversely impacted by the distance (travel time) of that area to customer's location. Although his model was utilized mostly for retail store location decisions, it was recently utilized for location decision of transportation hubs of an airline company (Eiselt and Marianov 2009). They used this model to optimize market share for a new coming airline company to a market competing with existing airline companies. Their model found locations for new hubs that maximized market share for the newcomer.

However, the model was limited to new-coming airline companies with no existing hubs. This work uses a similar technique to find with locations for new intermodal terminals for an intermodal service provider (Railway Company) with existing intermodal network.

2.3 DECISION MAKING UNDER UNCERTAINITY

Decision making environment is categorized as certainty, risk and uncertainty (Snyder 2006). Unlike a certain situation where all parameters are known, both risk and uncertainty conditions are random. Stochastic optimization problems pertain to risk situations where there is a known probability distribution for random/unknown parameters. The goal of this type of solutions is to optimize the expected value of an objective function. Under the uncertainty situation, the parameters are unknown and there is no information about their probabilities. Robust optimization arose to manage this type of problem with the goal of optimizing the performance of worst-case scenario.

Both methods attempt to find a solution which performs well under any realization of the unknown parameter. If the decision maker knows what probability distribution an unknown parameter follows, he can use stochastic optimization. Otherwise, robust optimization will be utilized by considering a set of scenarios for possible values of an unknown parameter. Robust optimization can address more problems despite its disadvantages. Its main drawback is identifying the appropriate number of scenarios which can comprehensively include all the possible future values of the unknown parameter(s). On the other hand, the final solution optimizes the worst-case scenario which may have a very low chance of occurrence. However, it is easy to implement and it allows the correlation of unknown parameters, which is not applicable for stochastic optimization. Including the scenarios with higher chance of occurrence can compensate the weakness of robust optimization. Scenario relaxation algorithms are also useful to expedite the solution time for these types of problems (Assavapokee et al. 2008). Real world historical freight data is not easily accessible. Hence it is not possible to draw the appropriate distribution for the uncertain parameters. Accordingly, this study utilizes the robust optimization to address multiple uncertainties in the developed models.

2.4 UNCERTAINITY IN INTERMODAL NETWORK DESIGN

Design decisions (as long term plans) affect the fluctuations of the problem parameters, such as cost, demand and supply over time. Moreover, these need huge investments with less flexibility for the change over time. On the other hand, it is hardly possible to accurately estimate the future values of unknown parameters. These confirm the need to include the uncertainty in design problems. This work considers the demand and supply uncertainties as discussed in the next sections.

2.4.1 DEMAND UNCERTAINITY

The demand for freight transport derives from commodity movements between shippers and receivers. Variations in economic conditions, technological innovations and market globalization lead to continuous fluctuations in freight demand over space and time as well as modal share changes for demand movements. More companies are becoming interested in intermodal option due to its cost, accessibility, and carbon emission benefits. Numerous models have been developed to forecast the future amounts and locations of freight demand, but their accuracy are still an unknown question (Lange & Huber 2015).

A few papers have considered the demand uncertainty in network design with consolidation centers (terminals/hubs). Marianov and Serra (2003) developed a stochastic model to find the location of hubs for an airline company. They assumed that passenger demand follows a Poisson distribution. They solved their model with a tabu search algorithm. Yang (2009) also considered the demand uncertainty in locating the hubs for an airline company. He used the historical data from air freight market in China and Taiwan and considered three levels for them (high, medium and low). Including the probabilities of occurrence of each demand level, the two stages stochastic model minimized the total fixed cost of opening hubs and expected routing costs of freight flow over the network. Alumur et al. (2012) were among the first researchers who utilized the robust optimization in hub network design problems. They included multiple scenarios to address uncertainty of the demand and set-up cost for hubs establishment. They showed how the results vary for an uncertain situation compared to deterministic cases. Ghaffari-Nasab et al. (2015) developed an alternate model for Alumur et al. (2012) by using a different robust optimization approach. They only included the demand uncertainty and added the capacity constraint at hubs to their model.

2.4.2 SUPPLY UNCERTAININTY

Capacity variations in network elements cause the supply uncertainty. These variations stem from scheduled or unscheduled events. Natural and/or human-made disasters are among the unscheduled cases which can cause the most dramatic changes in infrastructure capacities. On the other hand, maintenance and/or replacement projects due to aging of existing infrastructure are other sources of capacity reduction whose occurrences the network planner should know the time and location of. This study focuses on unscheduled events since those are unexpected and inevitable to happen. Moreover, losses and damages caused by these events may have a significant impact on economy of the disrupted area as well as other areas doing businesses with it. Additionally, that area takes a long time and needs a budget to recover from the disaster.

Ham et al. (2005) provided a brief overview of the impact of an earthquake in Midwest on economy of US. They mentioned that almost 40% of commodity flows in US pertains to Midwest, including the States of Illinois, Indiana, Iowa, Kentucky, Michigan, Missouri, Ohio, Tennessee and West Virginia. About 45% of these commodities are transferred between these states inside the Midwest region. The rest of commodities are transported/received to/from other states in the US. The New Madrid Seismic Zone located close to Memphis, Tennessee is a major earthquake zone which had the largest earthquake of the US history in 1811. If the same earthquake happens there, it can ruin the transportation network and production companies within the whole Midwest area. Limited accessibility to areas far from the disrupted region due to the disruption in transportation network affects the movement of commodities between the Midwest and the rest of US. The results showed that the value of commodity flow decreases by one billion dollars due to this earthquake. The mean shipment distance increases by 40 miles per shipment, which increases the transportation cost. Although it might not look significant, this will be remarkable for all the shipments through the whole network.

Pre-disaster and post-disaster mitigation strategies can reduce the vulnerability of the network to the unforeseen incidents. Pre-disaster (protection) strategies identify the most critical network components to reinforce them or adding new elements around them (i.e. adding new links) within a limited budget available for the project (Snediker et al. 2008). Post-disaster (recovery) actions use the limited recovery resources to reconstruct the disrupted components as well as keeping the disrupted network at its optimum service capacity during the recovery actions (Orabi et al. 2009). This study addresses the pre-disaster activities that can improve the network resiliency facing the future disruptions.

A remarkable number of researchers studied the disruption's impacts on transportation networks and analyzed the pre-disaster projects. They showed how the protection projects increased the network survivability and reduced the lost market as well as post-disaster reconstruction costs. In an early work, Sohn et al. (2003) investigated the impact of a hypothetical earthquake on demand loss of highway links. The analysis identified more critical links to retrofit so they stay resilient if an earthquake happens in future. Later in 2006, Sohn analyzed the impact of a hypothetical flood in highway networks of Maryland. To withstand the future floods, the different links were prioritized for retrofit based on distance-only and distance-traffic criteria.

To find the most critical links of a network at the time of a hypothetical disaster, Matisziw and Murray (2009) developed a mathematical model that evaluated the severity of absence of a link in the network performance. Their model found the links which maximized the commodity flow (connectivity) disruptions through the whole network. This objective identified the links which may have the worst-case effect on the network performance. To evaluate their model, they used the data of highway networks in the State of Ohio as a case study.

Research in intermodal network disruptions area is still in its early stages. In an earlier work, Miller-Hooks et al (2012) developed a mathematical model to identify which preparedness (pre-disaster) or recovery (post-disaster) activities to select in order to maximize the delivery of total demand to their destinations in case of disruptions. They assumed a limited budget for mitigation activities as well as limited capacities of network links and terminals. Burgholzer et al. (2013) developed a micro-simulation model to identify the higher-risk links in an intermodal network with both passenger and freight transport units. Unlike the previous studies, they simulated the transport of each individual unit to address the real-time congestion of network links due to the disruptions. For these situations, they also tracked the total delay and individual routes taken by each entity. In 2014, Marufuzzaman et al. formulated a multimodal biofuel supply chain system that considered the disruption risks in intermodal terminals. The objective was to minimize the total expected transportation cost in normal and disrupted situations as well as the fixed cost of opening new intermodal terminals. They tested their model on a new biofuel supply chain network in the US Southeast region (with high risk of hurricane and flooding). This case study concluded that their model preferred to locate the intermodal terminals far from the higher risk areas.

2.5 MULTI-PERIOD PLANNING

Expansion decisions are multi-period in nature since it may not be practical to build or expand enough terminals within a short time. The main reason is the limited investment budget in the beginning of planning horizon. On the other hand, the intermodal service provider will not invest until the adequate demand exists for its intermodal network. Multi-period programming helps the planner to gradually build the network over time. It breaks the planning horizon into multiple periods and identifies the optimum expansion plan at each period. This approach is beneficial in three folds. First, it removes the burden of huge capital investment for expansion of the whole network within a short time. Secondly, it provides the sufficient time for implementation of the expansion project without any interruptions in the network. Third, the investor can obtain the funds for expansion of network with the revenue generated from the goods transportation through its existing network. The expansion decisions are integrated with routing of freight flow over the network, which is more volatile to changing demand and capacity. Disruptions cause the variations of capacities. Multi-period planning expands the network over time so it can better incorporate the recovery progress of disrupted infrastructure for the flow assignment.

There are a few research papers in the field of multi-period hub location concept. Contreras et al. (2011) proposed the first model in this area. Their objective was locating a set of un-capacitated hubs in a network over the planning horizon. They identified the time of opening a hub and closing an open hub as well as allocation of the demand to the pairs of hubs in each period. There was no direct shipment option between a shipper and a receiver in their model. Later, Taghipourian et al. (2012) used the multi-period optimization to locate the virtual hubs in an airline network. Virtual hubs are spokes which become a hub when the major hubs are out of service due to disruptions. In their model, their hubs capacity is not limited and those hubs opened in one period might be closed in the next periods. Gelareh et al. (2015) proposed a multi-period hub location problem for a liner shipping provider. They assumed that hubs are not constructed in the liner shipping industry but are leased to the liner service providers by their owners. Their objective was identification of opening time, location and terms of contract of leased hubs. Alumur et al. (2015) proposed a multi-period model for single and multiple allocation hub location problems. They assumed that once a hub is opened, it never closes until the end of the planning horizon. They minimized the total fixed cost of opening new hubs, capacity expansion cost of existing hubs and transportation cost of the flow over the network. Their model did not include the direct shipping of a commodity between its origin and destination. To the extent of author's knowledge, there is only one work which studied the multi-period intermodal network expansion problem (Benedyk et al. 2016). They proposed a model to find the best expansion plan for each period by considering its variable demands. The strategic variables of this model were the location of new terminals and expansion sizes of existing terminals. Once these variables were determined, the OD pairs were allocated to the network.

Although multi-period planning can better incorporate the real world uncertainties, different time scales should be considered for strategic and operational decisions. Strategic decisions are more stable over time while operational decisions are variable (Nagy and Salhi, 2007). Albareda-Sambola et al. (2012) proposed a location-routing model with different time scales for location and routing decisions. In their model, the planning horizon is divided into multiple periods for routing decisions while location decisions are made in a subset of these periods. Up to now, there is no published research for the topic of multi-period planning with different time scales for intermodal hub network design and expansion problems.

2.6 CONTRIBUTIONS TO LITERATURE

Previous works have applied the operations research techniques to the intermodal network design and expansion problems. The current research has included the following considerations from the real-world for modeling of the intermodal network expansion problems.

1) competition of intermodal service providers (to maximize profit);

2) uncertainty in demand and supply (to minimize total cost) with robust optimization;

3) multi-period time frames for construction decisions. (to minimize total cost)

This dissertation also developed a number of meta-heuristic algorithms to solve the larger-size examples of these models. These contributions are addressed in the following research papers.

2.6.1 INTERMODAL NETWORK EXPANSION IN A COMPETITIVE ENVIRONMENT WITH UNCERTAIN DEMANDS

Contributions of this study to the literature are: by 1) a new mathematical model for intermodal network expansion, 2) incorporating competition between intermodal service providers, 3) including demand uncertainty in expansion decision, 4) developing a new SA algorithm to solve this model which could significantly reduce computational time compared to general optimization solvers, 5) studing practical aspects of the model using a real world case study to investigate model's real world application.

2.6.2 RELIABLE INTERMODAL FREIGHT NETWORK EXPANSION WITH DEMAND UNCERTAINITIES AND NETWORK DISRUPTIONS

This work contributed to the literature by: 1) a new integrated model for intermodal network expansion considering addition of new terminals, expanding existing terminals and retrofitting higher risk links of the network with a limited budget, 2) considering demand and supply uncertainties, 3) developing GA for strategic decisions with a new chromosome representation, 4) developing a new intermodal routing algorithm for freight flow assignment, 5) bringing practical aspects of the model by using a real world intermodal network and presenting managerial insights for intermodal service providers. The results verified that this model can significantly reduce future costs for the network planer if any disruption happens in the network.

2.6.3 RELIABLE MULTI-PERIOD INTERMODAL FREIGHT NETWORK EXPANSION PROBLEM

The last work in this dissertation improves the previous model by considering the following contributions: 1) considering multiple periods for expansion decisions, 2) assuming shorter periods for routing decisions, 3) proposing a new SA algorithm to solve the mathematical model proposed for this problem ,4) studying different practical aspects of the proposed model by using a real size case study and 5) proving the efficiency of multi-period decision making in total network costs and resource utilization compared to the existing models in the literature

CHAPTER 3: INTERMODAL NETWORK EXPANSION IN A COMPETITIVE ENVIRONMENT WITH UNCERTAIN DEMAND[1]

[1] Fotuhi F., N. Huynh. International Journal of Industrial Engineering and Computations. Vol. 6, no. 2, 2015, pp. 285–304. Reprinted here with permission of publisher.

ABSTRACT

This paper formulated robust optimization models for the problem of finding near-optimal locations for new intermodal terminals and their capacities for a railroad company, which operates an intermodal network in a competitive environment with uncertain demands. To solve the robust models, a SA algorithm was developed. Experimental results indicated that the SA solutions (i.e. objective function values) are comparable to those obtained using GAMS, but the SA algorithm can obtain solutions faster and can solve much larger problems. Also, the results verified that solutions obtained from the robust models are more effective in dealing with uncertain demand scenarios.

3.1 INTRODUCTION

Intermodal freight transport is the movement of goods in one and the same loading unit or road vehicle, which uses successively two or more modes of transport without handling the goods themselves in changing modes (United Nations, 2001). This research deals with the locations of rail-highway intermodal terminals where the modal shift occurs. A significant portion of the total cost and time in intermodal services is attributed to the drayage movements and intermodal terminal operations. Thus, the location of an intermodal terminal plays an important role in improving efficiency and attractiveness of intermodal services (Sorensen, Vanovermeire and Busschaert, 2012).

Most of the intermodal terminal location studies in the literature solve for the optimal locations without considering existing terminals in the network. This assumption is not realistic in practice as pointed out by Gelareh, Nickel and Pisinger (2010). In today' competitive environment, railroad companies are constantly looking to expand their intermodal networks to meet customers' demands and to increase market share. This is often accomplished by incrementally adding a few new terminals at a time. Solving the location problem that takes into account a company's existing terminals as well as those of competitors is more challenging. This study seeks to fill this gap in existing literature by developing a mathematical model that addresses competition in intermodal terminal location decisions. Competition involves new incoming terminals competing against existing terminals in the network for market share.

There are a few additional challenges involved in developing the proposed model. The first is uncertainty in demand. Demand for an intermodal terminal is the result of the commodity flow originated or terminated in the region where the terminal is located (Chiranjivi, 2008). Accurate long-range prediction of commodity flow is difficult because of uncertainty in economic situations and changes in supply chain decisions, infrastructure, and regulations. For example, most freight-related forecasts failed to predict the global recession that started in 2009. Thus, it is crucial for a strategic model to explicitly account for uncertainty in demand. The second challenge is determining the appropriate throughput capacity for the new terminal to avoid the situation of under-equipping the terminal which would lead to delays at the terminal (Nocera, 2009) or over-equipping the terminal which would lead to underutilized staff and resources. Throughput capacity is the total number of containers that can be processed by a terminal in a year and is usually expressed in TEUs (Twenty-foot Equivalent Units) (Bassan, 2007).

The objective of this work is to develop a mathematical optimization model which addresses all of the challenges and issues mentioned above. Specifically, the model seeks to determine the locations for the new intermodal terminals and their throughput capacities while considering competition and uncertainty in freight demands. The developed model contributes to the existing body of work on intermodal terminal location by explicitly incorporating competition and uncertainty in freight demand in the formulation. The proposed model is applicable for intermodal networks where private rail carriers are responsible for their own maintenance and improvement projects; the U.S. intermodal networks operate under this model.

3.2 LITERATURE REVIEW AND BACKGROUND

3.2.1 RAIL-HIGHWAY INTERMODAL TERMINAL LOCATION PROBLEM

Studies of terminal locations are performed at strategic planning level (Crainic, 1998) which involves different stakeholders with different objectives (Sirikijpanichkul and Ferreira, 2005). Over the years, the hub-based network structure has emerged as the preferred method for moving intermodal shipments (Ishfaq and Sox, 2011). A hub is a location where flow are aggregated/disaggregated, collected and redistributed (Arnold, Dominique and Isabelle, 2004). Similar to hubs, intermodal terminals are the transfer points at which containers are sorted and transferred between different modes (Meng and Wang, 2011). The emergence of hub based intermodal networks indicates that economies of scale are the principle force behind their preferred design (Slack, 1990). Also, because intermodal networks are combinations of their respective modal networks, it is natural that the hub network has emerged as the most suitable network design for intermodal logistics (Bookbinder and Fox, 1998).

In an intermodal hub network, smaller shipments are gathered and consolidated at distribution centers. At the next step, all consolidated containers are collected from these distribution centers and shipped to the terminals via drayage and then between a set of transfer terminals (i.e. rail-highway intermodal terminals). Finally, trucks transport loaded containers to their final destinations (Ishfaq and Sox, 2011). Rutten (1995) was the first to find terminal locations which will attract enough freight volume to schedule daily trains to and from the terminal. Arnold et al. (2004) developed a rail-highway intermodal terminal location problem with each mode as a sub-graph and considered transfer links to connect these sub-graphs to each other. Racunica and Wynter (2005) developed a model to find terminals in a rail-highway intermodal network. They considered a nonlinear concave-cost function to find these optimal hubs. Groothedde et al. (2005) developed a hub-based network for the consumer goods market. They compared the single highway mode with a highway-water intermodal. They showed that the intermodal approach is more effective than the unimodal approach (with just highway). Limbourg and Jourquin (2009) proposed a model to find hub locations in a rail-highway intermodal network. They developed a heuristic to find hub locations for a road network and found rail links which passes through these hubs. Meng and Wang (2011) proposed a mathematical program for a hub-and-spoke intermodal network. The main difference between their model and earlier works is that it considered more than one pair of hubs for moving containers from an origin to a destination. Their work considered a chain of terminals to move shipments with different types of containers.

Mode choice has been incorporated into the hub location models. Ishfaq and Sox (2010) developed an integrated model for an intermodal network dealing with air, highway and rail modes. Their model allowed for direct shipment between origin and destination pairs using highway. It found the optimal locations for intermodal terminals and distribution of shipments among pairs of intermodal terminals by minimizing the total transportation cost, transfer cost at the terminal and fixed cost of opening a hub. In their later work, they proposed a rail-highway hub intermodal location-allocation problem (Ishfaq and Sox, 2011). Their model found the optimal location of hubs as well as optimal allocation of shipments for an OD pair to selected hubs. Their model considered the fixed cost of opening a terminal, transportation cost, and the cost of delay at terminals. Sorensen, Vanovermeire and Busschaert (2012) modeled a hub-based rail-highway intermodal network with the option of direct shipment. Different fraction of shipments for an OD pair can use highway only or a combination of highway and rail (i.e. intermodal). Fotuhi and Huynh (2013) proposed a model which jointly selected terminal location, shipping modes and optimal routes for shipping different types of commodities. Their model allowed decision makers to evaluate scenarios with more than two modes.

3.2.2 TERMINAL THROUGHPUT CAPACITY

The traditional capacitated facility location problem in which facilities have limited capacities has been studied extensively. Drezner (1995) provided a survey of facility location studies with limited capacity. Some researchers have investigated the location planning problems with variable capacities. Verter and Dincer (1995) were the first to integrate location decision and variable capacity planning for a new facility. They developed a model to minimize the fixed cost of opening a new facility, variable cost for capacity acquisition, and total transportation cost. In the transportation domain, Taniguchi, Noritake and Izumitani (1999) were the first to integrate location decision and capacity planning (number of berths) for public logistic terminals in urban areas that serve only the truck mode. Their proposed model selected logistic terminals from a set of predefined candidate locations and found the optimal number of berths for each terminal. Tang et al. (2013) developed a model to find the best location for a logistics park, size of park and allocation of customers to it. They considered different layouts for the park and their model selected a lay out which can serve all demands. There has been limited work in capacity planning of intermodal terminals (Ballis and Golias, 2004, Nocera, 2009). To date, no study has examined intermodal terminal location and terminal size jointly.

3.2.3 COMPETITIVE LOCATION

All the aforementioned studies addressed the problem of designing a new network without consideration of existing road networks and rail terminals. In 1999, Marianov et al. developed a competitive hub location model that considered existing terminals in the network. They assigned the demand for each OD pair to a pair of potential hubs to maximize this newcomer’s market share. Transportation cost was the main factor for these assignments. In 2009, Eiselt and Marianov proposed a model of competitive hub location problem by incorporating a gravity model based on the work of Huff (1964). They allocated the demand to pairs of new hubs based on their attractions to maximize market share for the new hubs. Huff’s gravity model is a popular approach for estimating the captured market share by a facility. Based on this model, the probability that a customer chooses a facility is proportional to the attractiveness of the facility and is inversely proportional to the distance to the facility. Eiselt and Marianov (2009) mentioned that their model is suitable for a new incoming airline that has to compete with existing airlines. Chiranjivi (2008) studied the environmental impact of adding a new terminal to an existing rail-highway network. They introduced factors that made a terminal attractive and investigated the effects of the new terminal on accessibility and mobility of the intermodal network. Gelareh et al. (2010) studied the competitive hub location for a liner shipping network. They considered a newcomer liner service provider which has to compete with existing liner service companies. They introduced an attraction function to estimate the total captured market share by a new terminal by considering the travel time from the origin to the destination using that specific terminal and transportation rate. Lüer-Villagra and Marianov (2013) formulated a new competitive hub location problem to find optimal locations for a new airline company and optimal pricing to maximize their profits. They modeled consumers' behaviors using the Logit discrete choice model.

Table 3.1 provides a summary of capabilities of previous models and this study's proposed model, which extends the work of Eiselt and Marianov (2009) by considering more than one mode for a competitive p-hub network as well as uncertainty in demand. It enhances previous models in the area of intermodal terminal location problem by considering competition. As explained previously, competition involves new incoming terminals competing against existing terminals in the network for market share. Although Limbourg and Jourquin (2009) considered existing intermodal terminals in their model, they did not consider competition between the new terminals and existing ones. To our knowledge, competition has not been addressed in any intermodal network design studies. As indicated in Table 1, this paper advances the modeling of intermodal network design by considering competition and the joint location and terminal throughput capacity decisions. Additionally, it is the first intermodal network design study to use robust optimization to address uncertainty in demand. A brief overview of robust optimization as well as relevant literature is presented in the next subsection.

3.2.4 BACKGROUND (ROBUST OPTIMIZATION)

In developing models for real world systems, researchers often face incomplete and noisy data (Mulvey et al., 1995). To address uncertainty in data, researchers have developed a technique called robust optimization. It deals with uncertainty by considering a set of finite discrete scenarios for the parameter with noisy data and finds a solution that is near-optimal for any realization of scenarios (Snyder and Daskin, 2005).

Min-max regret and minimum expected regret are the two common robust optimization approaches (Kouvelis and Gu, 1997). To understand these approaches, consider a situation where S denote a set of s finite scenarios for the uncertain parameter and x represents a feasible solution for the robust problem. Let $Z_s(x)$ represents the solution of the feasible point x in scenario s and Z_s^* represents the optimal solution for scenario s (over all x). The min-max regret finds a solution which minimizes the maximum "regret" value for all scenarios and is formulated as follows.

$$\underset{x \in X}{Min}(\underset{s \in S}{Max}(Z_s(x) - Z_s^*)) \tag{3.1}$$

The "regret" represents the difference between $Z_s(x)$ and Z_s^*. For maximization problems, the regret is negative for each scenario; thus, for these problems, the objective of the robust model is to maximize the minimum regret. For situations where there is information about the probability of each scenario occurring, the minimum expected regret approach is preferred, which will find the near-optimal solution by minimizing the expected regrets over all scenarios (Daskin et al., 1997).

Table 3.1 Comparison of current paper's and related studies' capabilities

Reference	Model Features					Variables			Goals		
	Parameter		Competitive	Mode		location	capacity	allocation	responsiveness	profit	cost
	certain	uncertain		single	intermodal						
Marianov et al., (1999)	✓		✓	✓		✓		✓		✓	
Taniguchi et al., (1999)	✓			✓		✓	✓				✓
Arnold et al., (2004)	✓				✓	✓		✓			✓
Groothedde et al., (2005)	✓				✓	✓					✓
Racunica and Wynter (2005)	✓				✓	✓		✓			✓
Eiselt and Marianov (2009)	✓		✓	✓		✓		✓		✓	
Huang and Wang (2009)		✓		✓		✓		✓	✓		
Limbourg and Jourquin (2009)	✓				✓	✓					✓
Gelareh et al., (2010)	✓		✓	✓		✓		✓		✓	
Ishfaq and Sox (2011)	✓				✓	✓		✓			✓
Meng and Wang (2011)	✓				✓	✓					✓
Makui et al. (2012)		✓		✓		✓		✓	✓		
Sorensen et al., (2012)	✓				✓	✓		✓			✓
Lüer-Villagra and Marianov (2013)	✓		✓	✓		✓		✓		✓	
Current paper		✓	✓		✓	✓	✓	✓	✓		

There are a few studies in the literature that have utilized robust optimization to address uncertainty for hub location problems. Huang and Wang (2009) were the first to use robust optimization to find the near-optimal hub-and-spoke network design for an airline given uncertain demands and costs. They developed a multi-objective model and minimized total cost for all scenarios. Makui et al. (2012) developed a robust optimization model for the multi-objective capacitated p-hub location problem to deal with uncertainty in the demands for each OD pair and the processing time for each commodity at a hub. In the area of competitive location problem, Ashtiani et al. (2013) were the first to develop a robust optimization model for the leader-follower competitive facility location problem. This class of problems deals with the situation where the leader and follower have existing facilities, and the follower wants to open some new facilities, but the number of new facilities for the follower to open is uncertain. The objective of the leader-follower model is to maximize the market share for the leader after the follower has opened its new facilities.

3.3 MODELING FORMULATION

Consider a railroad company's rail-highway intermodal network that has competing railroad companies' infrastructure. Let $G(N_1, A_1)$ and $G(N_2, A_2)$ represent road and rail networks, respectively. Thus, N_1 represent cities, and N_2 represent intermodal terminals in the rail network. Similarly, A_1 represent the highway links in the highway network, and A_2 represent the railway links in the rail network. A shipment from origin *i to* destination *j* can be transported either directly by truck only via links on A_1 or by a combination of truck and rail (i.e. intermodal). The intermodal option involves trucks transporting cargo from origin i to terminal k via links on A_1, then trains transporting cargo from terminal k to terminal m via links on A_2, and finally trucks transporting cargo from terminal k to destination j via links on A_1. Let W represent the set of selected OD pairs with demands between them from N_1 cities.

Suppose a railroad company decided to expand its network by opening q new terminals from N_{new} candidate locations. It wants the new terminals to attract as much demand as possible (i.e. increase its market share). However, the railroad company already has N_{eo} terminals in the proximity of the market area for candidate locations and its competitors have N_{ec} terminals in the same area. Although there are more terminals operating in the network, the new incoming terminals only have to compete against those in the sets N_{eo} and N_{ec}; it is assumed that only those terminals located in the proximity of the candidate locations will have a direct impact on the market share of new incoming terminals. Thus, N_2, as defined previously, includes the railroad company's and competitors' existing terminals around candidate locations, the new terminals at candidate locations, and all other terminals in the network. Logically, the company should locate the new terminals at some distance, *M*, away from its existing ones to avoid serving the same market. Note that *M* may have different values based on the demographics of different parts of the network. According to Cunningham (2012) *M* has a value of 100 miles for the Eastern parts of the U.S. and 250 miles for the Western parts. Thus, the decision that the railroad company has to make is where to open the new terminal(s). Let this decision be defined by the binary decision variable y_k, which is equal to 1 if the candidate terminal $k \in N_{new}$ is selected. In a prescreening process, candidate terminals with a distance of less than M from the company's existing terminals are excluded from the list of eligible candidate terminals. If location k is selected, then the binary decision variable x_{km} indicates whether there is a connection between terminals k and m. If neither k nor m is open, then x_{km} cannot be 1. For existing terminals (k,m), x_{km} is 1.

Shipments going from origin i to destination j can be transported via multiple routes if there are several intermodal terminals available. The utility (i.e. attractiveness) of the intermodal option via the pair of terminals (k,m) for shipments going from origin i to destination j can be defined as follows.

$$u_{ijkm} = \frac{1}{(d_{ik} + d_{km} + d_{mj})^{\alpha}} \tag{3.2}$$

where d_{ik} and d_{mj} denote the delivery and pickup drayage distances, respectively, and d_{km} is the line-haul distance. The term α in Equation 3.2 can be used to give less significance to those facilities that are far from the origin and/or destination (Huff, 1964). In this study, a simple inversely proportional relationship is assumed; thus α is set to 1. Similarly, the utility of the truck-only option for shipments going from origin i and destination j is defined as follows.

$$v_{ij} = \frac{1}{d_{ij}} \tag{3.3}$$

The Huff gravity functions, Equations 3.2 and 3.3, can be used to compute the utilities of the two competing modes, intermodal and truck-only. Using these utilities, the probability that a shipper chooses a particular mode can be calculated using the Logit choice model. The probability that a shipper uses the intermodal option via terminals (k,m) to transport cargo from origin i to destination j is:

$$p_{ijkm} = \frac{u_{ijkm} x_{km}}{\sum_{(k \text{ or } m) \in \{N_{new}\}} u_{ijkm} x_{km} + \sum_{(k,m) \in \{N_2 - N_{new}\}} u_{ijkm} x_{km} + v_{ij}} \tag{3.4}$$

Similarly, the probability that shippers choose the truck-only option to move their cargo is:

$$p_{ij} = \frac{v_{ij}}{\sum_{(k \text{ or } m) \in \{N_{new}\}} u_{ijkm} x_{km} + \sum_{(k,m) \in \{N_2 - N_{new}\}} u_{ijkm} x_{km} + v_{ij}} \tag{3.5}$$

It is assumed that all demands are met. That is, for a specific OD pair (*i,j*), the sum of all probabilities is equal to 1 ($\sum_{(k,m)} p_{ijkm} + p_{ij} = 1$).

In this study, we accounted for the fact that future freight demand is uncertain and that we have a finite set of demand scenarios. Let these scenarios be denoted as $S = \{1..s\}$. The demand for OD pair (i, j) under scenario s is denoted as h_{ij}^s. The probability that demand between nodes i and j is served by the intermodal option via terminals (k, m) is p_{ijkm}. It follows that the total demand (i.e. market share) captured by terminals (k, m) for OD pair (i, j) under scenario s is $h_{ij}^s p_{ijkm}$. The higher the probabilities for pairs of terminals (k, m) as computed by Equation (3.4), the more demand the company will attract and thus increase its market share when either k or m is a new terminal.

In addition to determining the locations for the new terminals, our model also seeks to determine the annual throughput capacity, z_k, for the new terminal k which depends on its total attracted demand. This capacity needs to be sufficiently large to accommodate all demand scenarios. The objective of this problem is to maximize the new terminals' profits for all scenarios by maximizing the minimum regret. The revenue generated by terminal k per container is denoted as r_k. It is a fee that a shipper pays to the terminal for handling the container. There is an annual fixed cost f_k to operate the terminal, in addition to an operating cost c_k for handling the container.

3.3.1 MATHEMATICAL FORMULATION

The mathematical model for the max-min intermodal terminal location problem in a competitive environment can be formulated as follows (P1).

P1:

$$Max\, Z \tag{3.6}$$

$$\sum_{(i,j)\in W,(k \text{ or } m)\in N_{new}} h_{ij}^s p_{ijkm} r_k - \sum_{k\in N_{new}} f_k y_k - \sum_{k\in N_{new}} c_k z_k - O_s^* \geq Z, \qquad \forall s \in S \tag{3.7}$$

$$p_{ijkm} = \frac{u_{ijkm} x_{km}}{\sum_{(k \text{ or } m)\in N_{new}} u_{ijkm} x_{km} + \sum_{(k,m)\in\{N_2 - N_{new}\}} u_{ijkm} x_{km} + v_{ij}}, \qquad \forall (i,j)\in W, (k \text{ or } m) \in N_{new} \tag{3.8}$$

$$\sum_{k\in N_{new}} y_k = q, \tag{3.9}$$

$$x_{km} \leq y_k, \qquad \forall k \in N_{new}, m \in N_2 \tag{3.10}$$

$$x_{km} \leq y_m, \qquad \forall m \in N_{new}, k \in N_2 \tag{3.11}$$

$$\sum_{(i,j)\in W, m\in N_2} (p_{ijkm} h_{ij}^s + p_{ijmk} h_{ij}^s) \leq z_k, \qquad \forall k \in N_{new}, \forall s \in S \tag{3.12}$$

$$y_k, x_{km} \in \{0,1\}, z_k \geq 0, \qquad k \in N_{new}, m \in N_2 \tag{3.13}$$

The objective function (3.6) maximizes the minimum regret. O_s^* in constraints (3.7) is the optimal objective function for scenario s that is obtained by considering scenario s alone. The regret associated with each scenario is the difference between the total profit of new terminals comprising all scenarios and O_s^*. Constraints (3.7) show that each scenario's regret is greater than a minimum regret. Constraints (3.8) compute the probability that the intermodal option is used with the demand allocated to each pair of open terminals. Constraints (3.9) guarantee that q terminals will be selected. Constraints (3.10) and (3.11) ensure that the variable x_{km} is 0 if either terminal k or m is not selected. Constraints (3.12) define throughput capacities of selected terminals. Constraints (3.13) define the range of the decision variables. To obtain the regret of scenario s in constraints (3.7), O_s^* is determined by solving the following model (P2).

P2:

$$O_s : Max \sum_{(i,j)\in W,(k \text{ or } m)\in N_{new}} h_{ij}^s p_{ijkm} r_k - \sum_{k\in N_{new}} f_k y_k - \sum_{k\in N_{new}} c_k z_k \tag{3.14}$$

s.t: $Eqs.(3.8)-(3.13)$

The first term in objective function (3.14) is the total revenue generated by the new terminals. The second term is the annual fixed cost of operating the terminals, and the third term is the variable cost of operating the terminal.

If the decision maker knows the probability of each scenario occurring, then the objective of the robust optimization model would be to minimize the expected regret. As mentioned previously, the regret for problems with maximization objective is negative so the robust model's objective function is to maximize the expected regret. If scenario s occurs with probability β_s and R_s shows its related regret, then the maximum expected regret model is defined as follows (P3).

P3:

$$O_{\exp} : Max \sum_s \beta_s R_s \tag{3.15}$$

s.t: $$\mathrm{R_s} = \sum_{(i,j)\in W,(k \text{ or } m)\in N_{new}} h_{ij}^s p_{ijkm} r_k - \sum_{k\in N_{new}} f_k y_k - \sum_{k\in N_{new}} c_k z_k - O_s^*, \quad \forall s \in S \tag{3.16}$$

$Eqs.(3.8)-(3.13)$

$O_{\exp}$ in Equation (3.15) maximizes the expected regret over all scenarios and R_s in Equation (3.16) is the regret of each scenario.

3.4 SOLUTION METHOD

The aforementioned model is a nonlinear integer program, which is NP-hard (Krumke, 2004) and is not solvable by standard Mixed Integer Nonlinear Programing solvers (Eiselt and Marianov, 2009) while it may be possible to find the exact solutions for realistic-sized problems by exhaustive enumeration, such an approach will likely take days to solve, even with today's high performance desktops and workstations. For this reason, there is an increasing body of work that focuses on researching efficient algorithms using meta-heuristics such as tabu search and genetic algorithm to find the exact solutions for strategic problems (e.g., Ishfaq and Sox, 2011, Meng and Wang, 2011). In this research, a simulated annealing algorithm is proposed to find the optimal solutions for the three models discussed above: P1, P2 and P3.

3.4.1 BACKGROUND ON SIMULATED ANEALING (SA) ALGORITHM

Kirkpatrick, Gelatt and Vecchi (1983) were the first to propose SA to solve combinatorial optimization problems. The SA algorithm begins with an initial feasible solution and then its neighborhood is randomly searched for improvement. If the objective function improves, the solution is accepted and it becomes the new solution from which the search continues. Otherwise, it will accept a non-improving solution with a probability determined by the Boltzmann function $\exp(-\Delta/T)$, where Δ is the difference between the objective functions of two consecutive iterations and T is the temperature at that iteration. This probability is high at the beginning of the algorithm. It increases the chance of accepting a worse solution to avoid getting trapped in a local solution, but it decreases as the algorithm proceeds (i.e. cools down to its frozen temperature). Readers are referred to Kirkpatrick et al. (1983) for a complete description of the SA algorithm.

For SA, the cooling schedule requires a starting temperature T_0, cooling rate γ, maximum number of iterations at each temperature $K_{\max}$ and the stopping number σ. T_0 is selected so that the probability of accepting non-improving solutions is P_0. A number of non-improving neighborhoods for the initial solution which is a fraction of the neighborhood size (5% to 10%) are evaluated and their average cost increase (for cost minimization problems) $\overline{\Delta C}$ is computed. Then T_0 is computed based on this formula $\exp(-\overline{\Delta C}/T_0) \approx P_0$ [39]. A simple decay function of the parameter γ updates the temperature at the end of each epoch *r*; i.e. $T(r+1) = \gamma T(r)$. The value of γ is typically between 0.85 and 0.95, with higher values generating more accurate results but with a lower convergence rate. The number of iterations $K_{\max}$ is determined by the neighborhood size. The algorithm terminates when no improvement is found in a specific number of temperatures σ.

SA has been applied to a number of facility location problems and hub location problems (Murray and Church, 1996, Ernst and Krishnamoorthy, 1999, Arostegui et al., 2006). Drezner et al. (2002) were the first to apply SA for solving Huff-like competitive facility location problems. They proposed five different algorithms and showed that SA has promising results. The next subsection discusses how the SA algorithm was applied to solve the developed models.

3.4.2 PROPOSED SIMULATED ANEALING ALGORITHM

In this subsection, how the SA was adapted to solve P2 is first discussed. Then, how it was modified to solve P1 and P3 is presented.

A feasible solution for P2 is any configuration of q new terminals and their capacities. Thus, among the candidate locations, the ones that are furthest from the company's existing terminals are selected as the initial set of terminals. In this problem, constraints (3.10) and (3.11) may be replaced by the following equation:

$$x_{km} = \min\{y_k, y_m\} \qquad \forall (k \text{ or } m) \in N_{new} \tag{3.17}$$

Equation (3.17) indicates that x_{km} values are determined based on the initial terminal set. The parameters u_{ijkm}, p_{ijkm} and z_k are computed based on y and x values. u_{ijkm} values are determined based on the distances to terminals regardless of the terminal being open or not; thus, they remain constant through the end of the algorithm. The complete neighborhood for a solution is the set of all solutions found by closing one terminal and opening a closed terminal from the set of unselected terminals. For this problem, the neighborhood size is $q*(N_{new} - q)$. Given an incumbent solution, one of the neighboring solutions is selected by closing the terminal with the highest fixed and variable costs and opening a candidate terminal that is furthest from the set of unselected terminals. From this new terminal set (solution), the x_{km}, p_{ijkm} and z_k values are computed and objective function (3.14) is evaluated.

For this problem, 10% of a neighborhood is evaluated to compute T_0. Initial testing found that the SA algorithm obtained optimal solutions for small cases with $\gamma = 0.9$ and

$\sigma = 3$. Thus, these values were used for larger problems as well, but with a small increase in σ based on the problem size. The overall algorithm for P2 is outlined in Figure 3.1.

$T \leftarrow T_0$, $O^* \leftarrow O_{initial}$, $y \leftarrow y_{initial}$, $K \leftarrow 1$, $\sigma_0 \leftarrow 0$,

$\sigma_{\max}$: Non improving temperatures $O_{best} \leftarrow O_{initial}$, $T_{\min}$: Frozen Temperetaure

---

Repeat while $T > T_{\min} or\ \sigma_0 < \sigma_{\max}$

Repeat while $K \le K_{\max}$

$(y_{new}, z_{new}, O_{new})$ = Generate a neighborhood

$\Delta = O_{new} - O^*$

If $\Delta \ge 0$

$y \leftarrow y_{new}, O^* \leftarrow O_{new}$

Else if $e^{-\Delta/T} \le rand$

$y \leftarrow y_{new}$

End

If $O_{best} = O^*$

$\sigma_0 = \sigma_0 + 1$

Else

$O_{best} = O^*$

End

$K \leftarrow 1, T = \gamma T$

Figure 3.1 Simulated annealing algorithm for solving P2.

The SA algorithm discussed above can also be used to solve P1 and P3 with a minor change. The capacity constraints (3.12) in P1 and P3 determine the throughput capacity of open terminals under each scenario. It should be sufficiently large to accommodate any realization of demand values; thus, at each iteration of the SA algorithm the throughput capacity z_k for terminal k with $y_k = 1$ is computed as $\max_S(\sum_{(i,j)\in w, m\in N_2}(p_{ijkm}h_{ij}^s + p_{ijmk}h_{ij}^s))$.

3.5 COMPUTATIONAL EXPERIMENTS

The SA algorithm was coded in MATLAB R2012a, and the developed algorithm for P2 was tested on several randomly generated networks. Its performance was compared against GAMS/BARON solutions. The Branch-And-Reduce Optimization Navigator (BARON) is a GAMS commercial solver designed to find the global solution of Non-Linear Programs (NLP) and Mixed Integer Non-Linear Programs (MINLP) (Sahindis, 2013). All experiments were run on a desktop computer with an Intel Core 2 Duo 2.66 GHz processor and 8 GB of RAM and their computational times were reported.

Table 3.2 Values of parameters used in numerical experiments.

Parameter	Value
Highway miles	Normal(1,000, 100)
Line haul miles	Normal(700, 100)
Drayage miles	Normal(450, 100)
Fixed cost ($ per year)	Uniform(10,000, 30,000)
Variable cost ($ per container)	Uniform(10, 20)
Revenue ($ per container)	Uniform(20, 30)
Distance (miles) between competing terminals (existing and new)	Normal(400, 100)
Demand (containers)	Uniform(100, 300)

In order to examine the performance of SA for P2, 20 experiments with different problem sizes were randomly generated. The parameters for these problems are given in Table 3.2. These values were selected to reflect real world scenarios. The size of the test networks range from 4 to 15 existing terminals, 2 to 15 candidate locations, and 1 to 4 new terminals to open. Theoretically, q can be changed from 1 to *N_new*. However, in reality, it is likely that the number of terminals that can be opened and be profitable based on the demand OD pair pattern, shipper's expenditures, existing terminals in the market area, and terminal costs will be fewer than N_new. Thus, for each test network, only a limited range of q is solved to find their optimal locations.

Table 3.3 summarizes the results of the test problems. Column 1 indicates the experiment number. Columns 2, 3, and 4 show number of existing terminals in the competition area, number of existing terminals far from the competition area, and number of candidate locations for the new terminals, respectively. q in column 5 indicates the number of new terminals to be opened. Columns 6 and 7 show the objective function values found by SA (Z_{SA}) and GAMS (Z_{GAMS}) respectively. Column 8 shows the gap between the Z_{SA} and Z_{GAMS}; gap is computed as $100*(\frac{z_{GAMS}-z_{SA}}{z_{GAMS}})$. The last two columns show the execution time in seconds of SA (t_{SA}) and GAMS (t_{GAMS}), respectively.

It can be seen in Table 3.3 that the developed SA obtained the same objective function values as GAMS for all experiments. The asterisk in column 6 indicates that the network with the corresponding q new terminals yield the optimal profit. For example, for a network with 5 existing terminals and 5 candidate locations (experiment number 6 to 9), 3 new terminals yield the maximum profit for the company. The execution times indicated that the SA algorithm can obtain solutions in much shorter time than GAMS for larger problems. The execution time for GAMS grows exponentially with the problem size. It takes more than 6 hours for GAMS to find the optimal solution for a problem with 50 OD pairs, 10 existing terminals and 15 candidate locations for the new terminals while SA obtains the same results in a few seconds. GAMS was not able to obtain a solution for problems with more than 10 existing terminals and 15 candidate locations due to out of memory error. To show the application of the developed model for larger problems, the two case studies discussed in the next subsections are solved using our developed SA method.

3.5.1 LARGER SIZED INSTANCES

The robust models P1 and P3 were applied to two larger-sized case studies. The first case study involves an actual intermodal network in the U.S. and a set of freight demand scenarios derived from the Freight Analysis Framework (FAF3) (Battelle, 2011). The FAF3 database is provided by the U.S. Department of Transportation and it provides estimates of freight tonnage, value, and domestic ton-miles by region of origin and destination, commodity type, and mode, as well as state-to-state flows. To demonstrate the usability and generality of the developed model and solution approach, the second case study uses a larger random network configuration, as well as random demand volume and OD patterns.

3.5.1.1 CASE STUDY 1

This case study involves an actual intermodal network in the U.S., east of the Mississippi River. In the study area, there are two Class 1 railroad companies, A and B. Company A is considering expanding its network by adding a new terminal in South Carolina (SC). The candidate locations are Greenville, North Augusta, Lexington, and Florence. According to FAF3, these cities have the highest freight flow in South Carolina. They also have a good accessibility to interstates. Currently, both railroad companies have 4 to 5 terminals in South Carolina and neighboring states and a total of 18 in the study network. The goal of this analysis is to identify the optimal location for the new terminal and its throughput capacity. Figure 3.2 depicts the study area.

Table 3.3 Performance of SA compared against GAMS for test problems.

Exp. (1)	$N_{existing-competitin}$ (2)	$N_{existing-other}$ (3)	N_{new} (4)	q (5)	Z_{SA} (6)	Z_{GAMS} (7)	Gap (8)	t_{SA} (s) (9)	t_{GAMS} (s) (10)
1	2	2	2	1	6,810*	6,810	0	1.6	1
2	2	2	2	2	1,425	1,425	0	1.2	0.55
3	3	2	3	1	17,715	17,715	0	2.6	14.18
4	3	2	3	2	25,205*	25,205	0	3.1	14.45
5	3	2	3	3	19,816	19,816	0	3.05	37
6	3	2	5	1	18,558	18,558	0	2.09	25.3
7	3	2	5	2	25,194	25,194	0	2.18	27.1
8	3	2	5	3	26,133*	26,133	0	2.15	28.2
9	3	2	5	4	18,859	18,859	0	2.1	32
10	4	5	6	1	21,548	21,548	0	2.33	367
11	4	5	6	2	32,354*	32,354	0	2.19	440
12	4	5	6	3	31,097	31,097	0	2.44	520
13	5	7	8	1	24,494	24,494	0	3.7	3663
14	5	7	8	2	39,303*	39,303	0	2.97	3605
15	5	7	8	3	31,850	31,850	0	2.6	3720
16	7	8	10	1	14,214	14,214	0	3.4	15121
17	7	8	10	2	20,343*	20,343	0	3.25	14700
18	7	8	10	3	19,384	19,384	0	3.29	16850
19	7	3	15	1	4,802*	4,802	0	3.2	18050
20	7	3	15	2	1,272.6	1,272.6	0	5.6	25265

*Optimal for specified network

The analysis considered only domestic shipments that would use the intermodal option, which are those that need to be transported more than 750 miles and has an annual tonnage of more than 125 tons (ITIC manual, 2005). Live animals/fish, specific agricultural products, meat/seafood, alcoholic beverages, pharmaceuticals, plastics/rubber, wood products, newsprint/paper, paper articles, printed products, base metals, machinery, and furniture are the non-eligible commodities for intermodal transportation, and thus, were excluded from the analysis. After disaggregating the FAF3 data for 2040 using the proportional weighting method and using population as the surrogate variable, 482 eligible OD pairs were identified from/to SC counties to/from 16 states outside SC. Considering an average of 80,000 lbs as the maximum allowable weight for a 40-foot container, FAF3 commodity flows were converted to their equivalent container units.

Figure 3.2 Map of study area for case study 1.

Figure 3.3 shows the quantity of 2040 demand in number of containers for SC counties. As shown, Greenville, Charleston and their neighboring counties have the highest forecasted freight movement. Lexington and Richland counties are also forecasted to have high freight movement. Cost-of-living index was used to determine the relative relationship between the fixed costs and operating costs between the four candidate locations. Based on this index, Lexington is the most expensive county and parameters for the other three locations were computed based on the index. Google Maps was used to determine the drayage and line-haul distances.

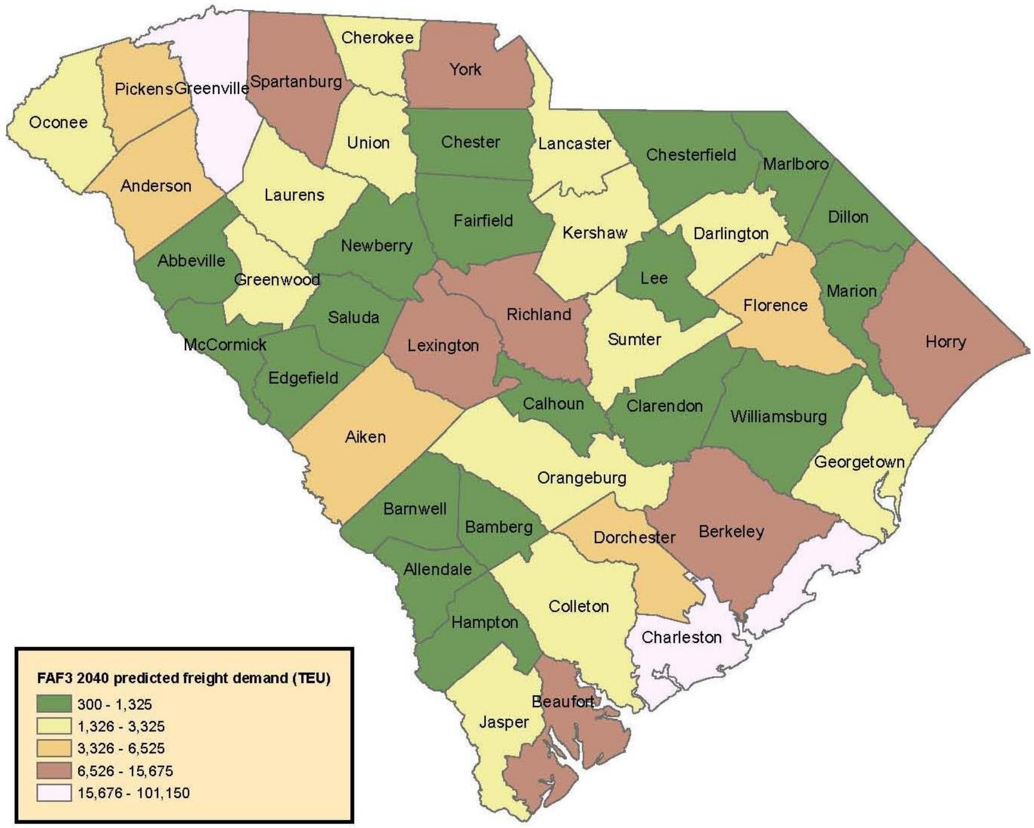


Figure 3.3 FAF3 2040 predicted freight demand for SC counties.

Ten demand scenarios were considered, based on the FAF3 predicted values for 2040. Scenario 1 is the FAF3 2040 demand estimate. Scenarios 2 to 4 are those with demands 5, 10 and 20% over the 2040 estimate. Scenarios 5 to 7 are those with demands 5, 10, and 20% under the 2040 estimate. Scenarios 8 to 10 considered the possibility of new developments that may take place in the industrial counties.

Table 3.4 shows the best location and its associated capacity for each scenario. If investment decisions are made using only the 2040 forecasted demand, then Greenville with a throughput capacity of 41,176 TEUs is the optimal location and size. However, that is not the case when other demand scenarios are considered, as illustrated in Table 3.4. If a terminal with a capacity of 41,176 TEU is built (based on the 2040 demand estimate) and scenario 2 occurred, then the terminal will not have enough capacity to meet the demand, 43,235 TEUs. This result shows that decision makers need to explicitly account for the different demand scenarios. The analysis showed that even if company A had the budget to build more than one new terminal, building just one new terminal is optimal because the profit decreases with each additional terminal.

Table 3.4 Results for individual scenarios.

Row	Scenario	Selected terminal	Capacity (TEU)
1	FAF3 predicted demand for 2040	Greenville	41,176
2	5% increase in the demand for 2040	Greenville	43,235
3	10% increase in the demand for 2040	Lexington	44,850
4	20% increase in the demand for 2040	Lexington	48,927
5	5% decrease in the demand for 2040	Greenville	39,118
6	10% decrease in the demand for 2040	Greenville	37,059
7	20% decrease in the demand for 2040	Greenville	32,941
8	50% increase in the demand in Charleston, Horry, Beaufort and Berkeley counties	Lexington	46,595
9	50% increase in the demand in Lexington, Richland and Aiken counties	Greenville	42,960
10	30% increase in the demand in Greenville, Spartanburg, York, Richland, Lexington, Charleston, Berkeley, Beaufort and Horry counties	Lexington	50,215

Table 3.5 presents the results for the robust models P1 and P3. Column 1 shows how many scenarios are considered for each experiment. Column 2 shows which scenarios are considered, i.e. 1-3 refers to scenarios 1 to 3. Columns 3 and 4 indicate the optimal objective functions for P1 and P3, respectively. The selected site by P1 and P3 are presented in columns 5 and 6 and their associated capacities are shown in columns 7 and 8, respectively. The last two columns show the execution times of P1 and P3, respectively. Greenville is the optimal location, but its capacity changes with inclusion of different scenarios in the decision for both models. These results indicated that the demand scenarios play a key role in determining the throughput capacity of the terminal for both robust models. It is noted that in scenario 1 (row 1 of Table 3.4), almost half of the freight

demands reside in the northern counties (i.e. Greenville, Spartanburg, York, Pickens and Anderson). Thus, Greenville was a suitable location to meet the demand for scenario 1 since it is located furthest north among the candidate locations.

Table 3.5 Solutions of the robust models: Z for P1 and O for P3.

# of scenarios	scenarios	Z^*	$O_{\exp}^*$	$y(Z)$	$y(O_{\exp})$	$z(Z)$	$z(O_{\exp})$	t_Z	$t_{O_{\exp}}$
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
2	1-2	-146690	-110020	Greenville	Greenville	43235	43235	8.62	7.26
3	1-3	-293380	-212850	Greenville	Greenville	45294	45294	9.71	9.04
4	1-4	-586760	-491980	Greenville	Greenville	49412	49412	10.14	10.31
5	1-5	-733460	-505480	Greenville	Greenville	49412	49412	11.36	11.83
6	1-6	-880150	-552190	Greenville	Greenville	49412	49412	12.76	13.83
7	1-7	-1173500	-587500	Greenville	Greenville	49412	49412	15.18	14.55
8	1-8	-1173500	-508380	Greenville	Greenville	49412	49412	48.78	16.35
9	1-9	-1173500	-476940	Greenville	Greenville	49412	49412	50	17
10	1-10	-1267200	-432180	Greenville	Greenville	50726	50726	87	20

To illustrate the impact of probabilities on site selection using P3, a set of four scenarios (1, 8, 9 and 10) with various probabilities was considered and the results were compared to those obtained by P1. Recall that Greenville was the optimal site for P1 regardless of probability values. It can be observed in Table 3.6 that Greenville is the optimal location with higher probabilities for scenarios 1 and 9, but Lexington became the optimal site when scenarios 8 and 10 have higher probabilities (highlighted in Table 3.6). This is because of the higher freight demands in central and southern counties (Richland, Lexington, Charleston, Berkeley, Beaufort and Horry) in scenarios 8 and 10. These results verified that demand scenarios and their probability values are significant factors in site selection.

Table 3.6 Impact of scenario probabilities on terminal selection.

Experiment	Scenario probabilities				Selected Terminal
	Scenario 1	Scenario 8	Scenario 9	Scenario 10	
1	0.5	0.1	0.1	0.3	Greenville
2	0.4	0.1	0.1	0.4	Greenville
3	0.3	0.1	0.1	0.5	Greenville
4	0.2	0.1	0.1	0.6	Greenville
5	0.1	0.1	0.1	0.7	Lexington
6	0.1	0.3	0.2	0.4	Lexington
7	0.2	0.15	0.05	0.6	Lexington

3.5.1.2 CASE STUDY 2

While case study 1 involves an actual intermodal network, its characteristics led to predictable results. To gain additional insights, case study 2 used a random network with various scenarios of OD pair patterns and demand volumes. The random network, generated on a 1,000 by 1,000 miles grid, has 15 existing terminals and 15 candidate locations. The objective was to find the optimal locations for up to 5 new terminals and their corresponding throughput capacities. Figure 3.4 depicts the intermodal network utilized in case study 2, with the 15 candidate locations (with their IDs labeled) and 15 existing terminals. It was assumed that there exists 20 cities, located randomly within a radius of 100 miles around each existing and candidate terminal. Given a combined total of 30 existing and candidate terminals, there is a total 600 cities in the intermodal network. The locations of the cities, represented by (x, y) coordinates, were generated as follows.

$$x = x_t + \beta\cos\theta, \qquad y = y_t + \beta\sin\theta$$

where β is a random number between 0 and 100 which defines the distance (in miles) between the city and the terminal t, and θ is a random number between 0 and 360 degree. (x_t, y_t) denotes the coordinates of the terminal t. 1000 OD pairs were randomly generated from the 600 cities with a Euclidean distance of more than 500 miles because the intermodal option is not applicable for shorter distances. Note that although there are 15 existing terminals in the network, each candidate terminal only has to compete with those located within a 300 miles radius from it.

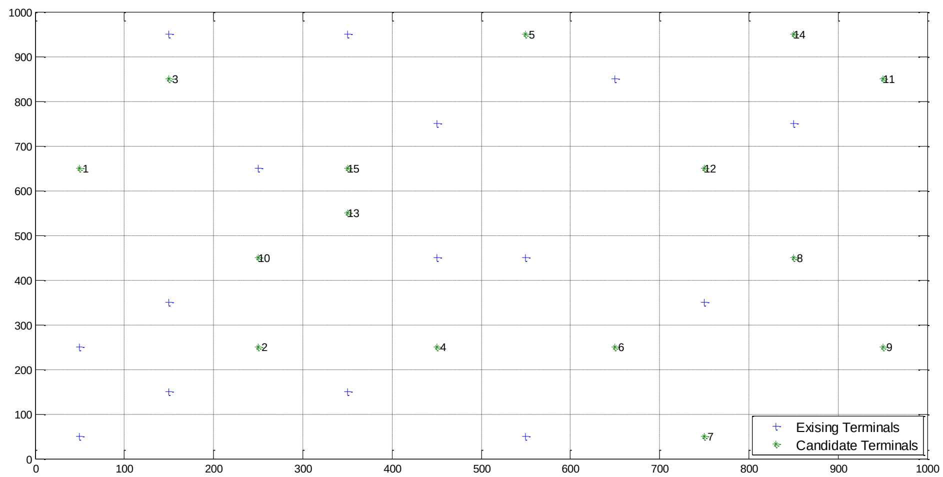


Figure 3.4 Network layout for case study 2.

Monte Carlo simulation was used to generate up to 45 scenarios for the OD patterns and their demand volumes. Each scenario involves a different set of OD demand patterns and demand volume. The OD pairs were randomly selected from the set of 600 cities, and the demand volume was randomly generated from the distribution U[1,000, 30,000]. The case study consists of 9 experiments, with experiment 1 having 5 scenarios and each subsequent experiment has an additional 5 scenarios. It was assumed that shippers will not select the intermodal option if it has a drayage distance (either pickup or delivery) of more than 250 miles.

Table 3.7 presents the results of the case study. Column 1 shows the experiment number. Column 2 presents how many scenarios were considered for the robust problem. Columns 3 and 4 present the optimal terminals and their sizes, respectively. The results show that locations 9 and 11 were never selected because they are located in isolated areas of the network. Since they both have a much smaller market, it would not be profitable to open new terminals at these locations. On the other hand, locations 4, 7, 8, 10 and 15 were included in the optimal set in more than 50% of the experiments. Due to the randomness in OD patterns, the decision of where to locate new terminals is more complicated than when the OD patterns do not change. The results indicate that as the number of scenarios increases, the results of the robust model becomes more consistent. It be can be seen in Table 3.7 that as the number of scenarios gets higher, the solutions converge to a set of similar candidate locations. Specifically, it indicates that regardless of the scenario, candidate terminals 4, 7, 10 and 15 should be selected. An interesting observation from this case study is that the optimal locations could be identified using a smaller set of scenarios, but the optimal throughput capacities will need to use a much larger set of scenarios. In reality, it is unlikely to have scenarios where the OD demand patterns and demand volume differ drastically. Thus, it is expected that the developed robust model will be able to identify both optimal locations and terminal sizes using a relatively small number of scenarios.

Table 3.7 Solution of the robust model P1 for case study 2.

Experiment #	# of scenarios	Selected terminals	Throughput capacity (TEU)
1	5	7, 10, 14	8,408,300; 4,445,800; 7,434,700
2	10	1, 4, 7, 10, 15	4,872,100; 2,817,200; 7,779,800; 5,130,000; 441,300
3	15	1, 6, 10, 14, 15	625,199; 7,735,600; 3,596,500; 6,790,600; 3,813,900
4	20	3, 4, 7, 8, 12	6,898,000; 4,335,000; 7,472,000; 15,674,000; 799,400
5	25	5, 8, 10, 12, 15	15,008,000; 73,300,000; 4,576,000; 7,224,000; 5,156,000
6	30	2, 7, 8, 10, 15	3,482,000; 8,353,000; 15,369,000; 4,119,000; 5,344,000
7	35	3, 4, 7, 8, 12	7,430,000; 4,469,000; 15,616,000; 7,961,000; 7,812,000
8	40	4, 7, 8, 10, 15	5,759,000; 15,224,000; 8,557,000; 5,436,000; 4,985,000
9	45	4, 7, 10, 13, 15	15,325,000; 15,623,000; 4,225,000; 3,481,000; 3,276,000

3.6 MANEGERIAL IMPLICATIONS

To gain insights on the implications of different managerial actions, two additional situations were analyzed. The first involves investigating the sensitivity of drayage distance on a terminal's ability to capture market share, and the second involves investigating the managerial option of closing an existing terminal and opening 1 or 2 new terminals at the candidate locations. The analysis was applied using the same network used for case study 1 and the 2040 FAF3 predicted freight flow for South Carolina.

In the proposed model, shipments going from i to j are allocated to terminals (k, m) based on their utility. The longer the drayage distances, from origin i to terminal k and from terminal m to destination k, the less attractive the terminal pair (k, m) is to shippers. To test the sensitivity of drayage distance on a terminal's ability to capture market share, we analyzed scenarios where shippers have a threshold on the maximum drayage distance they are willing to consider. In other words, we considered scenarios where shippers will only consider a terminal pair if their resulting drayage distances is less than their desired threshold. From the modeling standpoint, we effectively set the utility of terminals (k, m) to 0 if its drayage distances exceed the threshold. Table 3.8 presents the results of this analysis. Column 1 shows the different drayage distance thresholds considered. Column 2 shows how many new terminals will be opened. Columns 3 and 4 present the company's intermodal share and the competitor's intermodal share, respectively. Column 5 shows the remaining percentage of shipments using the truck-only option. The last column shows the obtained best locations for new terminals.

Table 3.8 Effect of drayage distance thresholds on intermodal market shares and locations

Drayage Distance threshold (miles)	# of new terminals	Own company's intermodal share	Competitor's intermodal share	Truck only modal share	Selected terminals
100	1	27%	19%	54%	Greenville
	2	33%	18%	49%	Greenville, Florence
	3	35%	18%	47%	Greenville, Florence, Augusta
	4	37%	17%	46%	All
250	1	50%	30%	20%	Lexington
	2	53%	27%	20%	Lexington, Augusta
	3	56%	24%	20%	Lexington, Augusta, Greenville
	4	59%	22%	19%	All
350	1	50%	31%	19%	Lexington
	2	53%	28%	19%	Augusta, Lexington
	3	56%	26%	18%	Lexington, Augusta, Greenville
	4	58%	24%	18%	All
500	1	51%	31%	18%	Augusta
	2	54%	29%	17%	Augusta, Lexington
	3	56%	27%	17%	Florence, Augusta, Lexington
	4	58%	25%	17%	All

It can be seen in Table 3.8 that when the drayage threshold is low (i.e. 100 miles), the truck uni-mode is generally preferred over intermodal. This is because the lower the threshold, the fewer opportunities there are for the intermodal option. In scenarios which have a higher number of new terminals, the railroad company has a better chance to increase its market share. The results indicate that when the drayage distance threshold ranges from 250 to 500, there is little difference in market share for intermodal and truck uni-mode. However, increasing the number of new terminals will increase the market share for the railroad company. It is also worth mentioning that different drayage distance thresholds affect the optimal location selection. As shown in Table 3.8, Greenville is the optimal terminal location when there is 1 new terminal and the drayage distance threshold is 100 miles, but Lexington becomes the optimal location when the drayage distance threshold is 250 and 350 miles. Thus, an important design consideration in determining the optimal locations is the shippers' drayage distance threshold. Such information could be easily obtained via survey and be incorporated into the model.

Typically, a railroad company would expand its network by opening new terminals. Another option the manager may want to consider is closing an existing terminal which is not attracting enough demand and opening new terminals in more attractive locations. Such a situation was investigated. Two sets of experiments were conducted. The first involves closing one existing terminal and opening one new terminal, and the second one involves closing one existing terminal and opening two new terminals. The base case (BC) scenario for the first set of experiments involves closing no existing terminal and opening no new terminal, and the BC for the second set of experiments involves closing no existing terminal and opening one new terminal. The results shown in Figure 3.5 indicate that by closing any of the existing terminals at the indicated locations (see x-axis labels) and opening 1 or 2 new terminals, the railroad company will gain market share compared to the base case. The only exception is Charleston. Note that the market share when closing the Charleston terminal is 49.2 % compared to 49.9% of the BC. Closing the terminal located in Atlanta has the highest impact on market share for both cases (opening 1 or 2 new terminals). This result suggests that Atlanta terminal is the least attractive terminal among the existing terminals. It should be noted that the greatest increase in the total market share is about 3% (scenario involving closing the Atlanta terminal and opening one new terminal). Thus, the manager will need to conduct a benefit-cost analysis to determine whether it is beneficial to close an existing terminal and open a new one.

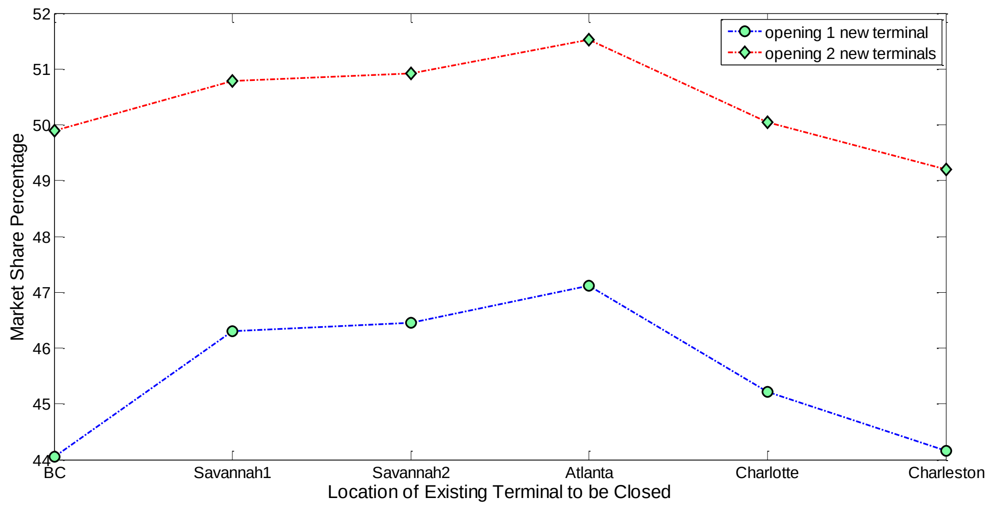


Figure 3.5 Change in market share by closing one existing terminal and opening new terminals.

3.7 CONCLUSIONS

This paper developed a mixed integer nonlinear programming model to find the best locations for new intermodal terminals and their capacities in a competitive environment with uncertain demand. Robust optimization models with min-max regret and minimum expected regret criteria were used to find solutions which are near optimal for any realization of demand scenarios. A simulated annealing algorithm was developed to solve the developed models. Computational experiments showed that the developed SA algorithm was able to find solutions with 0% gap compared to GAMS solutions, but in much shorter time for midsize problems. Moreover, the developed SA algorithm was able to solve larger-sized problems that GAMS could not (on a computer with 8 GB of RAM).

The results verified that location and capacity decision is more robust when considering different scenarios of freight demands.

This work contributed to the literature of intermodal terminal location problem by considering competition between existing terminals and new terminals, terminal capacity, and uncertainty in freight demands. In future work, there are several potential areas for improvement. In the area of competition, it could be enhanced by considering utility functions based on transportation rates and multi-period travel times. In the area of terminal capacity, it could be enhanced by considering capacity expansion for existing terminals based on predicted freight demands. Lastly, it could be enhanced by utilizing fuzzy or stochastic approaches to deal with uncertainty in freight demands.

While the proposed model and solution approach have been validated via case studies, key limitations should be considered when reviewing study results. These included: 1) choice of network topology and size, 2) accuracy of FAF3 predicted freight flows, 3) design of the scenarios and experiments, and 4) objective of the optimization model that considers only profit from the new terminal.

CHAPTER 4: RELIABLE INTERMODAL FREIGHT NETWORK EXPANSION WITH DEMAND UNCERTAINITIES AND NETWORK DISRUPTIONS[2]

[2] Fotuhi. F and Huynh. N. Networks and Spatial Economics, 2016, pp. 1-29. Reprinted here with permission of publisher

ABSTRACT

This paper develops a robust Mixed-Integer Linear Program (MILP) to assist railroad operators with intermodal network expansion decisions. Specifically, the objective of the model is to identify critical rail links to retrofit, locations to establish new terminals, and existing terminals to expand, where the intermodal freight network is subject to demand and supply uncertainties. Additional considerations by the model include a finite overall budget for investment, limited capacities on network links and at intermodal terminals, and time window constraints for shipments. A hybrid Genetic Algorithm (GA) is developed to solve the proposed MILP. It utilizes a column generation algorithm to solve the freight flow assignment problem and a multi-modal shortest path label-setting algorithm to solve the pricing sub-problems. An exact exhaustive enumeration method is used to validate the GA results. Experimental results indicate that the developed algorithm is capable of producing optimal solutions efficiently for small-sized intermodal freight networks. The impact of uncertainty on network configuration is discussed for a larger-sized case study.

4.1 INTRODUCTION

A robust freight transport system is a key contributor to the success of the U.S. economy (Ortiz et al., 2007). However, the existing freight transport system is running at its capacity due to increase of trades and an aging infrastructure. Thus, it has a limited buffer to handle the severe disruptions (Ortiz et al., 2007). Disruptions can range from frequent events with short term impacts, such as adverse weather, accidents and loading/unloading delays at intermodal terminals, to catastrophic natural and man-made disasters with long term impacts which can drastically degrade the transport capacity (Ortiz et al., 2007; Miller-Hooks et al., 2012). Examples of catastrophic disasters with long term impacts are

Hurricane Katrina, which damaged the transportation infrastructure of Gulf Coast area (Godoy, 2007) and the West Coast port labor strike which disrupted the U.S. freight supply chain (D'Amico, 2002). Thus, in order for the freight transport system to be able to handle such disruptions, there is a need to increase its capacity by incorporating redundant resources and backup facilities, and retrofitting existing infrastructure (Peeta et al., 2010; Liu et al., 2009).

Intermodal network design is a strategic level planning problem which finds the location of intermodal terminals and assignment of freight flow to the network. Strategic planning decisions deal with network infrastructure creation or expansion (SteadieSeifi, 2014). SteadieSeifi et al. (2014) recently provided a comprehensive overview of models and algorithms developed for strategic, tactical and operational multi-modal freight transport planning problems. According to this review, most strategic studies neglected two important practical aspects. The first is that the design does not consider existing intermodal infrastructure, which is not realistic in practice. It is more realistic to expand an existing freight transport network rather than designing a system from scratch (Gelareh et al., 2010). The second is that prior strategic studies neglected the possible changes in demand and supply that may occur over the planning period. Demand changes are to be expected as a result of pricing and supply changes over time, as well as the influx of new users in the system (Melese et al., 2016). Also, as new terminals come online, demands and freight flow patterns may be very different from what was envisioned at the network design phase (Taner and Kara, 2015). This research seeks to fill these gaps by developing a mathematical model to address expansion of an existing intermodal freight network and making it reliable; reliability means that the network can continue delivering service when faced with shocks, such as influx in freight demands or disasters that reduce capacity of network links and intermodal terminals.

This study deals with a rail-road intermodal network expansion problem for a private rail carrier that is responsible for its own maintenance and improvement projects, typical of U.S. Class 1 railroads. The strategic decision involves identifying locations for the new intermodal terminals, expanding the existing terminals and retrofitting the existing rail links in the network to enhance its survivability, given a finite budget. The strategic decision will subsequently affect the operational decision concerning freight flow assignment through the network. Thus, the routing decision is factored in the investment decision in the proposed model. A robust optimization approach is utilized to account for forecast demand errors and potential supply disruptions. The optimal decision seeks to minimize the total expansion, transport and lost-sale costs of the railroad company; lost-sale cost is incurred to the railroad company when it fails to deliver shipments on time.

The rest of the paper is organized as follows. Section 2 provides a summary of related studies. Section 3 presents the developed mathematical model. Section 4 discusses the proposed solution algorithm to solve the model. Section 5 discusses the results of the numerical experiments. Lastly, Section 6 provides concluding remarks and future research.

4.2 LITERATURE REVIEW AND BACKGROUND

4.2.1 LITERATURE REVIEW

Intermodal network design has become an emerging body of research within the transportation field (Bontekoning et al., 2004). In an intermodal network, smaller shipments are collected and consolidated at distribution centers. Then, all consolidated shipments are loaded into containers and shipped to the intermodal terminals with trucks.

The containers are then transported to the destination intermodal terminal using modes other than truck (i.e. rail, air, or water). Finally, the containers are delivered to their final destinations with trucks (Ishfaq and Sox, 2011). In an early work, Arnold et al. (2004) developed a model to select optimal locations for rail-road intermodal terminals from a set of candidate nodes and to assign the freight flow in the network. They developed a heuristic which utilized a shortest path algorithm for each Origin-Destination (OD) pair. Racunica and Wynter (2005) proposed a model for rail-road intermodal hub-and-spoke network design with 0, 1, and 2 hubs. Groothedde et al. (2005) developed a hub-based network for a road-barge intermodal network and compared their results with a truck-only network. They showed that the road-barge network is more efficient when the demand is steady, while the truck-only network is more capable of handling variations in the demand. Limbourg and Jourquin (2009) proposed a model to find terminal locations in a rail-road intermodal network. Their proposed heuristic found terminals for a road network and found rail links which pass through these terminals (also referred to as hubs). Ishfaq and Sox (2010) developed a model for an integrated network of rail, road and air which sought to determine the optional terminal locations, modes of operation at each terminal, and allocation of freight flow to the selected terminals. Later, they proposed a rail-road intermodal network design model which incorporated the costs of establishment, transportation and delay at intermodal terminals. They used the all-or-nothing assignment approach to assign demands between a certain OD to one pair of terminals which could meet the required time window for the shipment (Ishfaq and Sox, 2011). Sorensen et al. (2012) enhanced the work of Ishfaq and Sox (2011) by incorporating the direct shipment option in their model. They also improved upon the all-or-nothing assignment approach by enabling the model to assign different fractions of shipments for an OD pair to truck-only or rail-road intermodal option. Vidovic et al. (2011) proposed a model to find optimal locations for intermodal terminals by considering the hub catchment area. They assumed that each terminal will attract the demand within a specific radius from it. They used simulation to come up with freight demand due to the limited real world freight data. Fotuhi and Huynh (2013) developed an intermodal model that considered more than two modes of transport. Their model jointly selected terminal location, shipping modes and optimal routes for shipping different types of commodities. Peker et al. (2015) proposed a data-driven approach to find optimal locations for transportation hubs based on demand density and spatial features of potential hubs. They used a clustering-based heuristic to find the optimal locations. Recently, Meng and Wang (2011) proposed a model for expanding an intermodal network and taking the existing infrastructure into account. They proposed a model to optimally expand existing links and transshipment lines, as well as establishment of new hubs and links given a limited budget, while minimizing the total transportation and expansion costs. Their work is the first study to address the intermodal network expansion problem. Fotuhi and Huynh (2015) proposed a model to find locations for new intermodal terminals by considering terminal's catchment areas, uncertain demand and competition in the network. In their study a private intermodal service provider assumed to expand its network and intend to attract more demand from a competing company that has overlapping service areas with it.

The aforementioned works did not consider the possibility of failures in network elements. However, the occurrence of natural or man-made disasters in any transportation network is inevitable. A number of researchers have studied vulnerability of uni-modal transportation networks where a disaster could significantly reduce the capability of network to meet the demands. Berdica (2002) studied a vulnerable road network as a system that is sensitive to disruptions which could cause significant reduction in accessibility and disturbances of traffic. D'Este and Taylor (2003) noted that it is important to identify and strengthen the weakest elements of a network to decrease its vulnerability. This is feasible by including reliability criteria in the network design decisions, such as what investments to make to strengthen the network pre-disaster and what investments needed to enhance post-disaster recovery (Dayanim, 1991).

In recent years, there is a growing body of work that addresses disruptions in the context of network design. Almost all of these studies considered uni-modal transportation networks with risk of link failures. In an earlier work, Rios et al. (2000) studied a capacitated network design problem with arc failure risk. Their model determined which set of links to open and determined their capacities so that the network survives disruptions, with the goal of fixed costs minimization. Viswanath and Peeta (2003) proposed a multi-commodity maximal covering network design model for identifying critical routes and retrofitting bridges on these routes within a limited budget for earthquake response. Garg and Smith (2008) formulated a survivable multi-commodity network design model with arc failures to determine which arcs to construct so that the network survives the future disruptions. In a more general work, Desai and Sen (2010) formulated a reliable network design model with arc failure risks which minimized network design costs as well as resource allocation cost of mitigating higher risk arcs. A few researchers have studied the retrofitting decision for the existing links of a network. These studies deal with the tactical planning problem of optimally using the existing infrastructure (SteadieSeifi et al., 2014).

Liu et al. (2009) developed a model to allocate limited budget to retrofit more critical bridges in a network. They assumed that if a bridge is retrofitted, it would not collapse in case of disasters. Peeta et al. (2010) also proposed a pre-disaster investment model to retrofit more critical links in a highway network.

Disruptions may also affect facilities in a network. Snyder and Daskin (2005) were among the first to study the reliable p-median and uncapacitated facility location problems with facility failures. Their models sought to find location of warehouses to minimize transportation cost in normal situations and expected failure cost in disrupted situations. They assumed that unreliable facilities have the same failure probability. Cui et al. (2010) relaxed the identical failure probability assumption in Snyder and Daskin (2005) and considered facility–dependent failure probabilities in their model. Shishebori et al. (2014) proposed a model for combined facility location and network design problem by considering system reliability. They assumed that failures only happen in network nodes. However, their model decided which facilities to open and which links to construct to compensate for disruptions. The risk of facility failures have also been addressed in the context of logistics and transportation network design. Peng et al. (2011) developed a reliable logistic network design model with supplier and distribution center failures. Hatefi and Jolai (2014) developed a reliable forward-reverse logistics network model with distribution center failure risk. They considered uncertain demand as well as possible disruptions in their model. An et al. (2011) developed a hub network design model with hub failures. Unlike previously mentioned studies, disrupted facilities in this work were transshipment nodes. Their model identified hubs that can serve as backup hubs for disrupted situations. Their model's objective sought to minimize the expected cost of routing all flows in normal situations as well as disrupted situations. Marufuzzaman et al. (2014) developed a model for biofuel supply chain design with intermodal terminal disruptions. Their model's objective was to find locations for intermodal terminals and bio-refineries while minimizing total establishment and transportation costs. The Miller-Hooks et al. (2012) study is the only prior work that considers disruptions of both links and nodes in a transportation network. They developed a stochastic two-stage model to allocate limited budget to improve the resiliency of an intermodal network by choosing a set of pre-disaster and recovery activities. This is a tactical planning model which aimed to improve the existing infrastructure.

This work extends the work of Meng and Wang (2011) by considering uncertainty in both demand and supply. Additionally, it combines the tactical planning retrofitting decisions addressed by Miller-Hooks et al. (2012) with the strategic planning decision. This is the first study to jointly address tactical and strategic decisions in the context of intermodal network resiliency. In summary, this work contributes to the literature of intermodal network design and expansion by including demand and supply uncertainties and incorporating retrofitting decisions in the design phase. As such, these are its technical contributions.

1. A new model for the intermodal freight network expansion problem that jointly considers strategic network decisions, tactical retrofitting decisions, and operational freight flow assignment.
2. A robust and reliable model for intermodal network design/expansion, which simultaneously takes into account uncertain freight demands and infrastructure disruptions.

3. A hybrid genetic algorithm that is capable of solving the proposed model for realistic-sized networks in a reasonable amount of time. A modified version of the well-known label setting algorithm is proposed to consider problem-specific constraints for routing decisions.

4.2.2 BACKGROUND (ROBUST OPTIMIZATION)

Robust Optimization (RO) is an approach to modeling optimization problems under uncertainty. Rather than treating the problem as stochastic, RO treats the problem as deterministic and set-based. That is, instead of seeking an optimal solution in some probabilistic sense, RO constructs a solution that is feasible for any realization of the uncertainty in a given set. The motivation for this approach is twofold. First, in many applications a set-based approach is appropriate for capturing parameter uncertainty. Second, RO makes the problem computational tractable.

One of the more common approaches in RO is min-max regret which was first developed by Kouvelis and Yu (1997). It finds the solution with less distance from the optimal values of all scenarios. This distance is called regret that is the loss incurred for not choosing the optimal design for each scenario. This criterion is suitable in situations where the decision maker may feel "regret" if he/she makes a wrong decision. Thus, he/she thus takes this anticipated regret into account when deciding a solution. For example, in finance, an investor may have the opportunity to invest in a number of portfolios. Under the min-max regret approach, he/she would choose a portfolio that minimizes the maximum difference between his/her portfolio's performance and that of other portfolios. In some situations, the min-max criteria is too pessimistic for those decision makers who are willing to accept some degree of risk because its solution is affected by the worst case scenarios which are sometimes unlikely to occur. However, this issue could be addressed at the modelling stage by including only relevant scenarios in the scenario set. The reader may refer to the work of Ben-Tal and Nemirovski (2002) and Bertsimas et al. (2011) for more information about robust optimization. The followings are basic principles of min-max regret.

Let S represent a set of s finite scenarios for an uncertain parameter (e.g. demand, link capacity) and x denote a feasible solution for the robust problem. $O_s(x)$ is the objective function value of scenario s at feasible point x and O_s^* is the optimal solution for scenario s (for all x in the set X). Regret is represented by the difference between $O_s(x)$ and O_s^*. The min-max regret obtains a solution which minimizes the maximum regret over all scenarios and is formulated as follows.

$$\underset{x \in X}{Min}(\underset{s \in S}{Max}(O_s(x) - O_s^*)) \tag{4.1}$$

A few studies in the literature have used the min-max regret approach for facility location and supply chain design problems (e.g., Daskin et al., 1997; Ramezani et al., 2013). To our knowledge, this is the first study to apply robust optimization to the intermodal network design and expansion problem.

4.3 MODELING FRAMEWORK

This section presents the formulation of the model that addresses the rail-road intermodal network expansion with network disruptions and demand variations. This model extends the classical intermodal network design problem by considering existing infrastructure. As explained previously, its goal is to identify locations for new intermodal terminals, existing terminals to expand, and rail links to retrofit so that the total transportation cost and lost-sales cost is minimized for normal and disrupted situations.

Consider a railroad company which intends to expand its intermodal network. The network representation for this company is given by $G(N, A)$, where N is the set of nodes and A is the set of arcs. G consists of sub-networks, $G(N_1, A_1)$ and $G(N_2, A_2)$ for road and rail networks, respectively. Transfer between modes takes place at intermodal terminals. N_1 represents cities, and N_2 represents intermodal terminals in the rail network. N_2 includes existing terminals (N_3) and candidate terminals (N_4). A_1 and A_2 represent highway and rail arcs, respectively. The network enables freight shipments to be transported between OD pairs represented by W either by truck-only or intermodal. A set of paths P_w comprising a chain of arcs is given for each OD pair $w \in W$. The travel time for an intermodal path is computed using the individual links' travel times and transfer times at intermodal terminals. Note that some paths might be infeasible due to time window constraints or because they include candidate terminals that have not been selected to be built.

The proposed model makes the following assumptions: (1) the expanded intermodal terminals, the newly established terminals, and the retrofitted rail links are able to withstand disruptions, (2) shipments with late delivery are considered as lost-demand and incur a penalty cost, (3) if the shortest path cost for a shipment is higher than the penalty cost for lost-demand, the shipment is considered as an unmet-demand, and (4) there is no delay for shipments passing through an intermodal terminal that do not require a changing of mode. It is assumed that a few expansion designs $l_j \in L_j$ with a given cost of C_{j,l_j} and capacity of v''_{j,l_j} are available for existing terminals $j \in N_3$. C_{j,l_j} denotes the cost for labor, equipment, and storage space to handle additional v''_{j,l_j} containers. S is a set of scenarios, each of which represents a normal or disrupted situation. Other parameters used in the formulation of the Reliable Intermodal Network Expansion Problem (RINEP) include:

Parameters

t_a: travel time on link a

τ_j: transfer time at intermodal terminal j

T_w: delivery due date for OD pair w

e_a: capacity of link a

ν_j: capacity of intermodal terminal j

β_a^s: disruption percentage for link a under scenario s

α_j^s: disruption percentage for terminal j under scenario s

B: available budget for investment decisions

d_w^s: demand of OD pair w under scenario s

F_j: fixed cost of opening a new terminal at location j

h_a: retrofitting cost for rail link a

δ_{ak}^w: path-arc incidence (= 1 if link a is used in path k for OD pair w; 0 otherwise)

υ_{jk}^w: path-terminal incidence (=1 if shipments change mode at terminal j in path k for OD pair w; 0 otherwise)

The decision variables are as follows.

Strategic and Tactical Decision Variables

$$y_j = \begin{cases} 1 & \text{If a terminal is opend at location } j \in N_4; \\ 0 & \text{Otherwise} \end{cases}$$

$$z_a = \begin{cases} 1 & \text{If link } a \in A_2 \text{ is retroffite d;} \\ 0 & \text{Otherwise} \end{cases}$$

$$v'_{j,l_j} = \begin{cases} 1 & \text{If expansion design } l_j \text{ is selected for existing terminal } j \in N_3; \\ 0 & \text{Otherwise} \end{cases}$$

Once the strategic and tactical decision variables are determined, the freight flow is assigned to the network. The flow assignment step considers the following decision variables which are scenario dependent.

$$x_k^{ws} = \begin{cases} 1 & \text{If } OD \text{ pair } w \text{ uses path } k \text{ in scenario } s; \\ 0 & \text{Otherwise} \end{cases}$$

f_k^{ws} : Amount of freight flow for OD pair w on path k for scenario s

<u>RINEP Formulation</u>

$$Minimize\ Z \tag{4.2}$$

Subject to:

$$\Big(\sum_{j \in N_4} F_j y_j + \sum_{j \in N_3} v'_{j,l_j} C_{j,l_j} + \sum_{a \in A_2} z_a h_a + \sum_{k,w} f_k^{ws} c_k\Big) - O_s^* \geq Z, \quad \forall s \in S \tag{4.3}$$

$$\sum_{w,k} f_k^{ws} \upsilon_{jk}^w \leq (1-\alpha_j^s) v_j + v''_{j,l_j} v'_{j,l_j}, \quad \forall j \in N_3, s \in S \tag{4.4}$$

$$\sum_{w,k} f_k^{ws} \upsilon_{jk}^w \leq v_j, \quad \forall j \in N_4, s \in S \tag{4.5}$$

$$\sum_{j \in N_4} F_j y_j + \sum_{j \in N_3} v'_{j,l_j} C_{j,l_j} + \sum_{a \in A_2} z_a h_a \leq B \tag{4.6}$$

$$\sum_{l_j} v'_{j,l_j} \leq 1, \quad \forall j \in N_3 \tag{4.7}$$

$$\sum_{w,k} f_k^{ws} \delta_{ak}^w \leq (1-\beta_a^s) e_a, \quad \forall a \in A_1, s \in S \tag{4.8}$$

$$\sum_{w,k} f_k^{ws} \delta_{ak}^w \leq (1-\beta_a^s(1-z_a)) e_a, \quad \forall a \in A_2, s \in S \tag{4.9}$$

$$\begin{aligned} &\sum_{a \in A_1} (1+\beta_a^s) t_a \delta_{ak}^w + \sum_{a \in A_2} (1+\beta_a^s(1-z_a)) t_a \delta_{ak}^w + \sum_{j \in N_3} (1+\alpha_j^s)(\tau_j \upsilon_{jk}^w) + \sum_{j \in N4} \tau_j \upsilon_{jk}^w \\ &\leq T_w + M(1-x_k^{ws}), \quad \forall w \in W, k \in P_w, s \in S \end{aligned} \tag{4.10}$$

$$f_k^{ws} \le M x_k^{ws}, \quad \forall k \in P_w, w \in W, s \in S \tag{4.11}$$

$$\sum_{w,k} x_k^{ws} \upsilon_{jk}^{w} \le M y_j, \quad \forall j \in N_4, s \in S \tag{4.12}$$

$$\sum_{k} f_k^{ws} = d_w^s, \quad w \in W, s \in S \tag{4.13}$$

$$y_j, z_a, v'_{j,l_j}, x_k^{ws} \in \{0,1\}, f_k^{ws} \ge 0, \forall w \in W, a \in A_2, j \in N_2, s \in S \tag{4.14}$$

The objective function (4.2) minimizes the maximum regret over all scenarios. Constraints (4.3) ensure that the regret for each scenario is greater than the minimum regret. Constraints (4.4) and (4.5) guarantee that the capacity of existing and new terminals are not violated, respectively. Constraint (4.6) ensures the amount of money used for establishment of new terminals, expansion of existing terminals, and retrofitting of rail links is within the available budget *B*. Constraints (4.7) ensure that at most one expansion design can be selected for existing terminals. Constraints (4.8) and (4.9) prevent highway and rail link capacities from being exceeded. Constraints (4.10) assign flows to the paths to meet delivery due dates. These constraints only hold if path *k* is used for OD pair *w*. Constraints (4.11) and (4.12) ensure that flows are assigned to selected paths and open terminals, respectively. Constraints (4.13) ensure that the total flow shipped over all feasible paths between an OD pair equals to the demand for this OD pair. Constraints (4.14) impose non-negativity and integrality on the decision variables. A Deterministic Intermodal Network Expansion Problem (DINEP) is used to obtain O_s^* for scenario *s* which can be expressed as follows.

DINEP:

$$O_s^* = Minimize \sum_{j \in N_4} F_j y_j + \sum_{j \in N_3} v'_{j,l_j} C_{j,l_j} + \sum_{a \in A_2} z_a h_a + \sum_{k,w} f_k^{ws} c_k \tag{4.15}$$

s.t.: (4.4)-(4.14)

The objective function (4.15) minimizes the total cost, which consists of the cost of opening new terminals, cost of expanding existing terminals, cost of retrofitting rail links, and transport cost.

4.4 SOLUTION METHOD

RINEP and DINEP are both classes of the discrete network design problem which is NP-hard (Meng and Wang, 2011). A few researchers have developed algorithms based on Lagrangian relaxation and Benders decomposition to solve the robust network design problems (Miller-Hooks et al., 2012; Snyder and Daskin, 2006a). These algorithms provide exact solutions; however, as the number of scenarios and network size increase the algorithm become less efficient. For larger-sized problems, it may take several days to find a feasible solution, with no optimality guaranteed (Miller-Hooks et al., 2012). In this paper, a new algorithm is proposed in an effort to identify more efficient solution algorithms for this class of problems. The proposed algorithm uses GA which has been widely implemented due to its ability to find optimal or near-optimal solutions for large-sized problems (Holland, 1975). Recently, a few researchers have used GA to solve the bi-level network design problems (Meng and Wang, 2011; Peng et al., 2011; Ko and Evans, 2007). In these papers, the strategic planning variables were first determined by GA, and subsequently the corresponding transportation sub-problems were solved using the problem-specific algorithms. A similar approach is adopted in this paper.

The proposed algorithm incorporates GA and the Column Generation (CG) method. The GA component is used to find values for the strategic decision variables. Once the values for these variables are determined, the flows are assigned to the network by solving a Capacitated Multi-Commodity Intermodal Network Flow Problem with Time Windows (CMCINFPTW) for scenario s to find O_s^*. The CG method is used to solve the CMCINFPTW. For the robust problem, $|S|$ CMCINFPTW are solved to find O_s. There are some differences in the GA component for solving RINEP and DINEP; these details are provided in subsequent sections.

4.4.1 CHROMOSOME REPRESENTATION

The proposed GA comprises a three-part chromosome with binary and integer genes to represent the strategic planning variables. The first part represents the set of candidate terminals to open. The second part represents the rail links to retrofit, and the last part represents the existing terminals to expand. Figure 4.1 illustrates the chromosome representation for a solution. As shown, this chromosome indicates that the problem deals with 3 candidate locations for new terminals, 8 rail links to be considered for retrofitting, and 3 existing terminals to be considered for expansion. The first part of the chromosome indicates that among the 3 potential locations, a new terminal should be opened at location 2 (=1). The second part of the chromosome indicates that rail links 3 and 8 should be retrofitted (=1). The last part of the chromosome indicates that expansion designs 2, 1, and 3 should be selected for the three existing terminals, respectively.

Note that in the formulation, binary variables are used to determine which expansion design to select for an existing terminal. Thus, an existing terminal with m available designs needs m binary genes. To reduce the number of genes in the chromosome, each gene in third part of chromosome stores an integer value rather than a binary value. The integer value denotes the expansion design to select for the existing terminal. Using this representation, for the example illustrated in Figure 4.1, the number of genes in the third part of the chromosome is reduced from 9 (3 terminals x 3 possible expansion designs) to 3.

0	1	0	0	0	1	0	0	0	0	1	2	1	3
Part 1			Part 2								Part 3		

Figure 4.1 Chromosome representation

4.4.2 INITIAL POPULATION GENERATION

Alander (1992) suggested that an appropriate population size for a problem with *n* decision variables in a chromosome is between *n* and 2*n*. Preliminary experiments were conducted over this range (*n* to 2*n*) and the results indicated that an initial population size of *n* is sufficient. For the robust model (RINEP), the initial population is generated by including the optimal chromosomes of each scenario which are obtained by optimally solving DINEP for each scenario separately. If the number of scenarios is more than *n*, then *n* scenarios are randomly considered for the initial population. If the number of scenarios is less than *n*, additional chromosomes are generated by using crossover and mutation operators to make the initial population size to be *n*. Chromosomes (i.e. solutions) that violate the budget constraint are discarded from a population.

4.4.3 GA OPERATORS

Roulette wheel selection and tournament selection are the two most common GA selection methods. In this study, the binary tournament selection method is used instead because it has been shown to generate better solutions for the class of problems considered in this study (Chu and Beasley, 1997). Preliminary experiments tested several crossover operators, including one-point crossover, two-point crossover, uniform crossover, and multipoint crossover. The two-point crossover with 0.8 crossover probability was found to generate better solutions and thus adopted in our solution approach. The mutation operation used in this study is that the binary genes have a probability of 0.1 to change from 1 to 0 or vice-versa and integer genes (in part 3 of chromosome) have equal probability of taking on a value from 0 to the number of available expansion designs.

4.4.4 FITNESS FUNCTION

The fitness value (i.e. the objective function value) can be determined given a chromosome (solution). In this study, the fitness value for RINEP and DINEP are computed using objective functions (4.2) and (4.15), respectively. Specifically, after obtaining a solution for the strategic problem (y, v', z), |S| CMCINFPTW are solved with CG to find flow assignment for demands between each OD pair. Once all the flows are determined, o_s can be computed using Equation (4.15) and regret values can be computed for each scenario using Equation (4.2).

As mentioned previously, by fixing the design variables (y, v', z), DINEP becomes CMCINFPTW. The CMCINFPTW finds the least cost paths for each OD pair such that the capacity of the arcs and intermodal terminals are not exceeded and no delivery delay is incurred. If no such path can be found, a penalty cost is incurred. This is accomplished by assuming that in the network there exists a hypothetical path between the origin and destination for the shipment, and that the path has infinite capacity and instantaneous travel time (Peng et al., 2011). The cost of the hypothetical path is set to be the penalty cost for each unit of unmet demand.

CMCINFPTW is a class of the well-known Capacitated Multi-Commodity Network Flow Problem (CMNFP) with additional constraints. CMNFP is NP-hard but can be solved by CG (Ahuja et al., 1993; Yaghini et al., 2012). CG incorporates a master problem which finds the optimal objective value by considering a portion of decision variables as basic variables and a pricing problem to find decision variables that can improve the objective function if they enter the basis. This study adapts the CG method proposed by Ahuja et al. (1993) to solve the CMCINFPTW for each scenario. Ahuja et al. (1993) stated that the pricing problem for CMNFP is a constrained shortest path problem; one for each OD pair which can be solved using the well-known label-setting algorithm from multi-period programming. Hence, an intermodal label-setting algorithm is proposed in this paper to solve CMCINFPTW.

4.4.4.1 INTERMODAL LABEL SETTING ALGORITHM

Cho et al. (2012) was among the first to propose a label setting algorithm for a multi-objective intermodal routing problem with time windows. Their algorithm sought to find the route with the minimum total cost and minimum travel time. It attached a label to each node which included travel time as a constraint and travel cost as the objective function. This study adapts their algorithm by adding "capacity" and "mode" to the label to enable the modeling of network disruptions as well as consideration of the transfer time and transfer cost at intermodal terminals. "Capacity" is used to check for possible disruptions of network elements (link or node). If the network element is not functional, then the label would contain a value of zero for capacity. "Mode" is used to determine if there is a change of mode at an intermodal terminal. If so, then the transfer time and transfer cost at the intermodal terminal are added to the path's cost and time. Nodes with a capacity of zero and/or a transfer time that leads to a violation of the time window constraints are eliminated from further consideration in the algorithm.

4.4.5 TERMINATION CRITERIA

A maximum of 100 (*Num_G*) generations is used as a termination criterion for the GA. The algorithm also terminates if it cannot improve the objective function value for 10 (k) consecutive generations. The key algorithmic steps are presented below.

Step 0: Set $t \leftarrow 0, k \leftarrow 0$

Step 1: Randomly generate n distinct chromosomes satisfying budget constraint. Compute fitness value for each chromosome. Let (y_t, v_t', z_t) be the best chromosome in the population; let (y^*, v'^*, z^*) be the incumbent solution (i.e., $(y^*, v'^*, z^*) \leftarrow 0$).

Step 2: If $f(y_t, v_t', z_t) < f(y^*, v'^*, z^*)$, then set $(y^*, v'^*, z^*) \leftarrow (y_t, v_t', z_t)$.

Step 3: Make a new generation by performing a two-point crossover with a probability of p_c and mutation with a probability of p_m on selected chromosomes with Binary Tournament selection. Check the feasibility of new chromosomes (discard those that violate the budget constraint). Compute fitness value of new chromosomes using Equation 15.

Step 4: Let $\Delta = (f(y_t, v_t', z_t) - f(y_{t-1}, v_{t-1}', z_{t-1})) / f(y_{t-1}, v_{t-1}', z_{t-1})$. If $\Delta < \varepsilon$ then set $k \leftarrow k+1$

Step 5: If $k = k_{\max}$ or $t = Num\_G$, go to step 6. Otherwise, let $t \leftarrow t+1$ and go to step 2.

Step 6: If $f(y_t, v_t', z_t) < f(y^*, v'^*, z^*)$, then set $(y^*, v'^*, z^*) \leftarrow (y_t, v_t', z_t)$ and return the best solution (y^*, v'^*, z^*).

Figure 4.2 represents a flowchart of the hybrid algorithm.

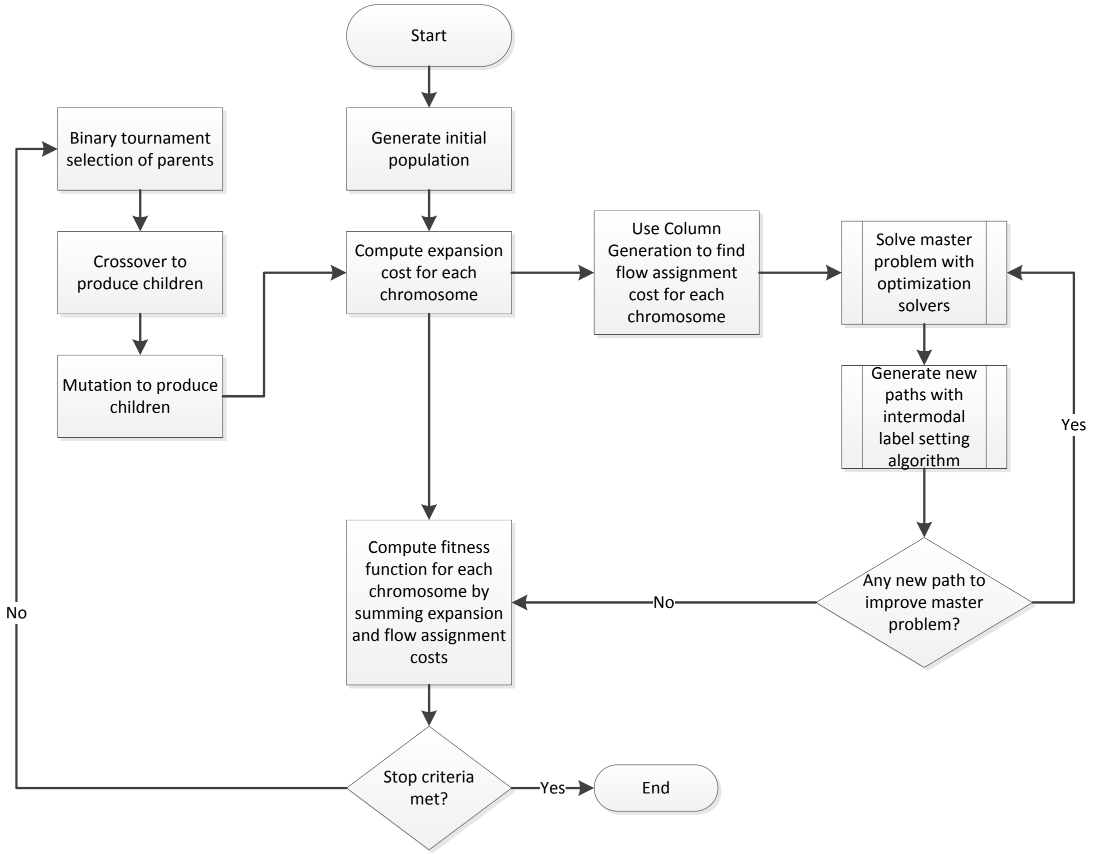


Figure 4.2 Flowchart of the hybrid GA_CG algorithm

4.5 NUMERICAL EXPERIMENTS

The proposed hybrid GA algorithm was coded using MATLAB R2014 and the experiments were run on a desktop computer with an Intel Core 2 Duo 2.66 GHz processor and 8 GB of RAM. A set of small-sized networks and a larger realistic-sized network were used to validate the proposed model and algorithm. The validation is done by comparing the GA results against the EE algorithm results in terms of computational time and objective function value.

4.5.1 SMALL SIZED NETWORK

To illustrate the consistency of the proposed model, a small hypothetical network is first presented and analyzed. Figure 4.3 depicts the network which includes three existing terminals (nodes 1 to 3), five candidate terminals (nodes 4 to 8), six cities (nodes 9 to 14) and thirty links. Five random OD pairs are selected from cities.

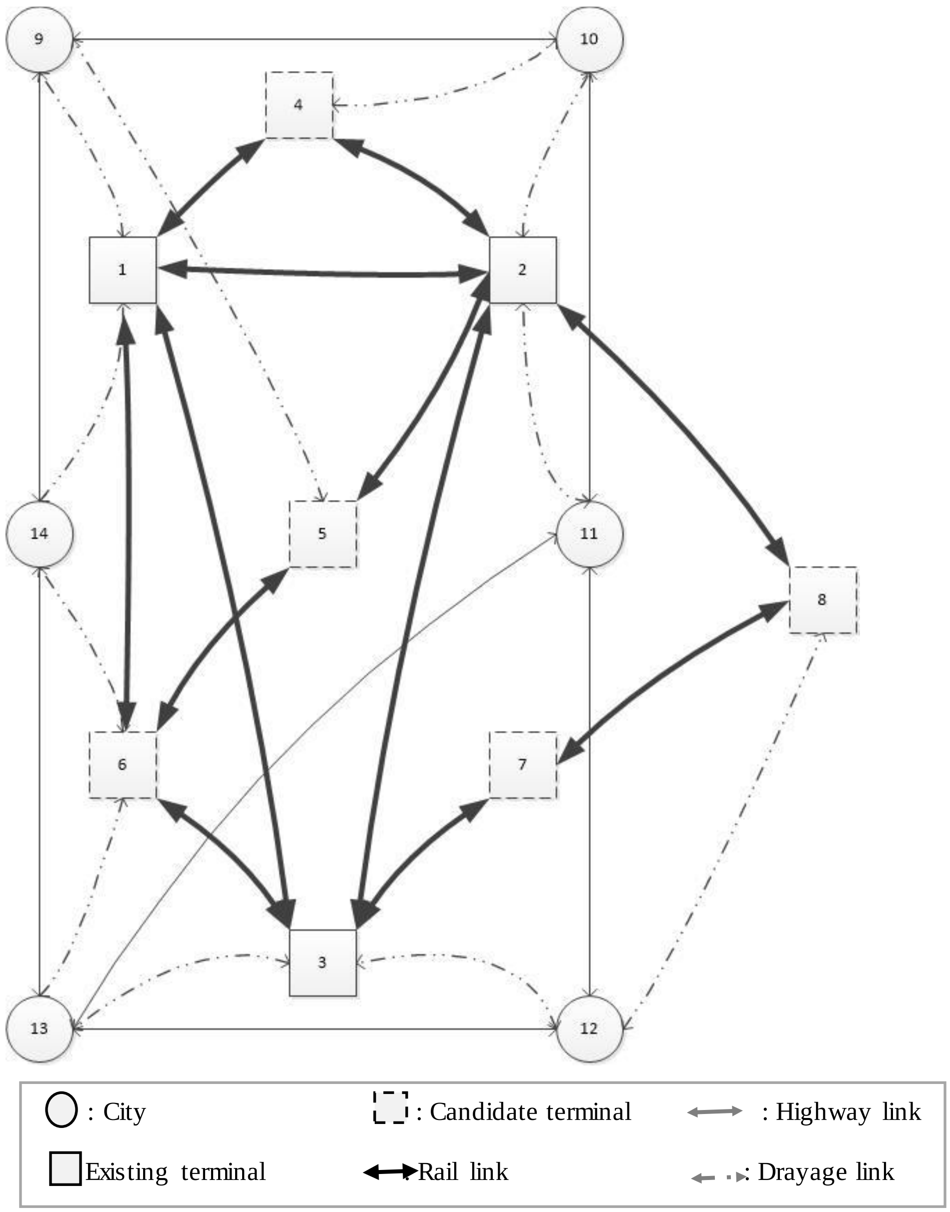


Figure 4.3 Network of the small case study.

Table 4.1 presents the parameters of the given network. An incident is assumed to happen in node 3 (existing terminal 3) that caused capacity reductions in the four rail links connected to this node as well.

Table 4.1 Values of parameters used in small networks

Parameter	**Value**
Travel cost of highway links	Uniform(2,4)
Travel cost of rail links	Uniform(0.1,1.1)
Transfer cost at intermodal terminals	Uniform(2,3)
Travel time of highway links	Uniform(1,3)
Travel time of rail links	Uniform(5,10)
Transfer time at intermodal terminals	Uniform(10,30)
Capacity of highway links	Uniform(1000,3000)
Capacity of rail links	Uniform(10000,20000)
Capacity of intermodal terminals	Uniform(30000,50000)
Fixed cost of opening new terminals	Uniform(500000,1000000)
Cost of retrofitting links	Uniform(300000,400000)
Cost of expanding existing terminals	Uniform(200000,300000)

The optimal solution includes building three new terminals in candidate nodes 5, 6 and 8 as well as expanding node 3 which is the disrupted node. Table 4.2 presents the routing results corresponding to each OD pair. Column 1 shows nodes selected as origins and destinations of ODs. Columns 2 and 3 depict total demand and delivery time window of each OD. Column 4 presents multiple paths found for each OD pair due to capacity limitations of nodes and links. Otherwise, each OD would only use its shortest path. Column 5, 6 and 7 show path cost and time and quantity of demand passing through each path, respectively. The travel time of selected paths are within the time window for each OD. Sum of column 7 which shows the quantity of the demand passing through the path of each OD equals with total demand of that OD. The initial capacity of node 3 was 31248 and 80% of it is assumed to decrease due to disruption. The remaining capacity is 6249. Regarding this limited capacity, only four paths with total flow of 3885 units pass this node in the final solution. To compensate the lack of node 3 capacity, a new terminal should be built in node 6 and node 3 terminal must be expanded.

To validate the GA algorithm for small size networks, five random networks with 6 to 20 highway nodes, 5 to 7 existing terminals, 3 to 7 candidate locations for new terminals, 30 to 100 links (including rail links), and 5 to 30 demand OD pairs were generated. Their parameters were selected as mentioned in Table 4.1.

Table 4.2 Routing results of the small case study

OD	Total Demand	Delivery Time Window (h)	Selected Paths	Path Cost	Path Travel Time (h)	Flow on Path
9-11	6395	122	9-10-11	6.11	4.51	1380
			9-1-2-11	9.59	56.81	1067
			9-10-2-11	7.42	6.02	20
			9-5-2-11	11.1	55.67	906
			9-14-13-11	10.41	7.06	1158
			9-14-6-13-11	11.71	8.66	629
			9-5-6-3-12-11	17.14	73.49	1022
			Lost demand	5000	0	211
12-9	15777	131	12-11-10-9	9.32	5.84	217
			12-3-6-1-9	13.21	75.59	1067
			12-3-6-5-9	13.93	72.16	275
			12-8-2-5-9	15.02	82.03	1252
			Lost demand	5000	-	12966
11-14	8600	121	11-13-14	6.8	4.74	2052
			11-2-1-14	9.62	57.27	1992
			11-13-6-14	8.1	6.34	900
			Lost demand	5000	-	3655
13-10	18272	123	13-11-10	6.68	5.47	1165
			13-6-1-2-10	13.28	83.37	724
			13-3-6-1-2-10	15.7	96.65	1521
			Lost demand	5000	-	14862
14-12	1403	132	14-13-12	6.24	4.29	894
			14-6-13-12	7.54	5.89	509
			Lost demand	5000	-	0

Table 4.3 shows the validation results for these five small-sized networks. Column 1 shows the structure of the network. The five numbers in the parenthesis denote the number of highway nodes, number of candidate terminals, number of existing terminals, number of links, and number of OD pairs. Columns 2 and 3 indicate the computational time of the GA and EE, respectively. Column 4 shows the gap between the GA objective function value and the EE objective function value. As shown, the proposed GA algorithm was able to find the same optimal solution as the EE algorithm, but in a much shorter time. The largest problem among these small-sized networks took the EE algorithm almost four days

to obtain the solution while the GA algorithm was able to obtain the same solution within a few minutes. These results demonstrate the efficiency and accuracy of the proposed GA for solving the DINEP.

Table 4.3 Comparison of proposed hybrid GA algorithm versus EE algorithm for solving DINEP

Problem Size	GA time (sec)	EE time (sec)	Gap (%)*
(6-3-5-30-5)	20	1,100	0.00
(10-5-5-50-10)	45	1,287	0.00
(20-5-7-100-20)	135	16,650	0.00
(20-5-7-100-25)	170	151,350	0.00
(20-7-7-100-30)	258	232,808	0.00
*Gap $= 100 * (Obj_{GA} - Obj_{EE}) / Obj_{EE}$			

4.5.2 LARGER REALISTIC-SIZE NETWORKS

To demonstrate the potential real-world application of the proposed model and algorithm, a test case is created using a realistic-sized intermodal and highway network and actual freight demands. As mentioned, RINEP and DINEP are both NP-hard problems and although EE is able to find the exact solution, a small increase in the network size will exponentially increase its computational time and/or lead to insufficient memory on a typical desktop computer with 8 GB of RAM (Meng and Wang, 2011). For this test case, the EE algorithm was unable to obtain a solution, and thus, only the GA results are reported.

The test case involves an intermodal network of a Class 1 railroad which operates in the Midwest and on the western side of the U.S. It is assumed that this company wishes to gain a competitive advantage by improving and expanding its network. Additionally, to make its business more attractive to shippers, this company wishes to strengthen its network to withstand demand variations and network disruptions. The options to strengthen the network include opening new intermodal terminals, expanding existing terminals, and/or retrofitting existing rail links.

This company currently has 20 terminals in its intermodal network and it is considering establishing new terminals at 10 potential locations. These candidate locations are chosen because they are located near areas with higher disaster risks or freight demands. As such, terminals at these locations could serve as backup terminals to deal with demand influx and disruptions. The network includes 45 major cities which are connected via U.S. interstates. Figures 4.4(a) and 4.4(b) show the intermodal rail network and the highway network used for the test case, respectively.

For the purpose of this test case, highway distances and travel times were obtained using Google Maps. Rail miles between intermodal terminals were obtained from the railroad company's website. It is assumed that the trains move at an average speed of 35 miles per hour. Terminals are assumed to operate 24/7 (24 hours per day, 7 days per week) and that shipments incur a 24-hour dwell time at the terminal. The dwell time is 30 hours for terminals that are opened 24/5. The various costs involved in intermodal transport were taken from the ITIC Manual (2005). These include $0.7 transport cost per mile for rail movements and $3.64 per mile for truck. A $150 transfer cost per container at an intermodal terminal is used based on a South Carolina freight study.

The test case used a set of freight demand scenarios from the Freight Analysis Framework (FAF3) (Battelle, 2011). Five demand scenarios were considered based on the FAF3 freight forecast demands for the years 2020, 2025, 2030, 2035 and 2040. The test case considers only those shipments that are likely to use intermodal transport, which are those with an annual tonnage of more than 125 tons and a distance of more than 750 miles

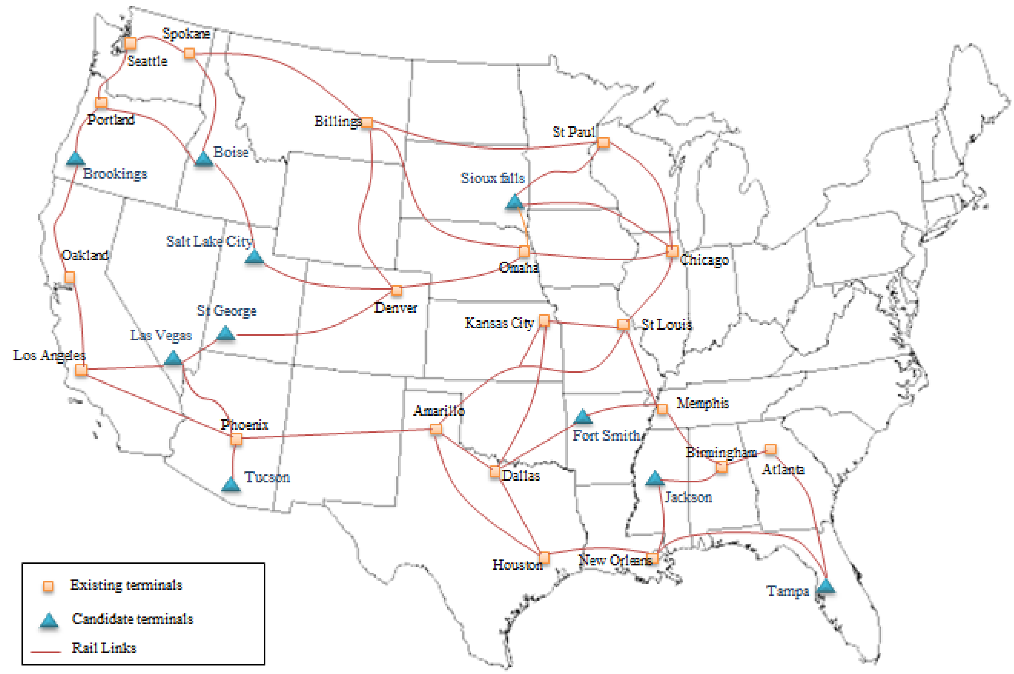
(ITIC manual, 2005). Assuming an average of 80,000 lbs. weight limit for a 40-foot container, FAF3 data were converted to their equivalent container units.

The test case considered eight disruption scenarios: (1) Burlington Rail Bridge collapse (in Iowa), (2) hurricane in Southeast, (3) tornado in Midwest, (4) earthquake in Northwest (Washington and Oregon), (5) ice storm in North and Midwest, (6) labor strike at Los Angeles and Chicago terminals, (7) disaster in Texas, and (8) rail maintenance in Texas and Arizona. For the scenarios with disrupted links, links which are directly connected to the disrupted links had their capacities reduced but their reductions were smaller than the disrupted links themselves. A total of 22 experiments involving different disruption and demand scenarios were considered. We first solved the discrete problem (DINEP) for the 22 experiments separately and then investigated the impact of integrating all experiments for the final decision using the robust problem (RINEP).

4.5.2.1 EXPERIMENTAL RESULTS FOR DISCRETE PROBLEM

To investigate the impact of expansion on cost savings, each experiment's optimal cost with expansion is compared against the total transportation cost of the experiment with no expansion (case 1) and expansion for only nominal-scenario (case 2); the nominal scenario is the scenario most likely to occur.

The results are shown in Table 4.4. Column 1 in Table 4.4 shows the experiment number. Column 2 provides the demand and disruption scenarios considered for the experiment.



(a)

(b)

Figure 4.4 Test case network: (a) Intermodal rail network; (b) Highway network

Column 3 provides the difference between the total transportation cost of No-expansion (case 1) for the experiment and the optimal cost of the experiment with expansion, column 4 provides the difference between the total transportation cost of the Nominal-scenario expansion (case 2) for the experiment and the optimal cost of the experiment with expansion, and column 5 presents the computational time of GA. The nominal scenario (Experiment #0 in Table 4.4) is one that considers the demand for 2040, but does not account for network disruption.

The results shown in Table 4.4 indicate that the railroad company will pay an extra $250 million (average value of column 3) on average annually if it does not strengthen its network to accommodate the growth in freight demand and future disruptions. This result suggests that doing nothing will end up costing the company a significant amount of money. By making some investments to strengthen the network to accommodate the nominal scenario, the cost difference decreases to $113 million (average value of column 4). These results indicate that it is better (less costly over the long run) for the railroad company to make the extra investments to strengthen the infrastructure than not to. Note that some experiments do not incur extra cost compared to the nominal scenario because their optimal expansion design is identical to that of the nominal experiment.

The optimal design of each scenario includes at most two new terminals. Brookings is selected in 90% (20 out of 22), Fort Smith in 18% (4 out of 22) and St. George in 10% (2 out of 22) of experiments. Since around 80% of demand originates or ends in California, a new terminal in Brookings as a backup for Los Angeles and Oakland will significantly reduce the burden of congestion in these two terminals to deal with fluctuations in demand and possible disruptions. Optimal links to retrofit and terminals to expand are more affected by disruption that are different for each scenario rather than demand fluctuations. The results of each disruption scenario are discussed in detail to justify this conclusion.

Experiment 1 considers scenario 1 with Burlington rail bridge collapse which makes the Omaha-Chicago rail link out of service. The optimal solution allocates budget to build a new terminal in Brookings and to retrofit Omaha-Chicago rail link. Brookings terminal will accommodate the growth in future demand and retrofitting of the disrupted link (replacing the bridge with a new one) will avoid the further collapse.

Considering experiment 2 with scenario 2 involving a hurricane in Louisiana and Florida (it specifically impacts New Orleans terminal and links in Louisiana and Florida), the optimal design concludes the establishment of two new terminals in Brookings and Fort Smith. The new terminal in Fort Smith provides extra capacity to an alternate route for the "Houston-New Orleans-Birmingham" route which is impacted by Hurricane and can be a backup terminal for New Orleans.

Scenario 3 includes tornado occurring in Oklahoma, Arkansas, Nebraska, Missouri, and Kansas states. It affects terminals in Omaha, Kansas City and St. Louis as well as multiple rail and highway links in those states. The optimal design opens a new terminal in Brookings, expands the terminal in Billings and retrofits six disrupted links. Expanding a terminal in Billings will provide more capacity for an alternate route. Retrofitting six disrupted links will mitigate the capacity reduction of these links in case of tornado.

The impact of expansion on network configuration can be understood by considering experiment 4 with demand values for 2040 and disruption scenario 4 (Earthquake in North part of Oregon and west side of Washington). In this scenario, the earthquake severely degrades the capacity of Portland and Seattle terminals, as well as their connecting rail links. It also reduces the capacity of highway links in those areas. The optimal solution indicates that the expansion should include building a new terminal in Brookings, OR and retrofitting the Portland-Seattle rail link. This is deemed reasonable as the Brookings terminal can be considered as a backup terminal for the Portland terminal and retrofitting Portland-Seattle link will ensure sufficient capacity to facilitate freight shipments to the Brookings terminal.

Experiment 5 is impacted by disruption scenario 5 which is an ice storm in Midwest of US. It impacts multiple states, including Utah, South Dakota, Wyoming, Montana, Nebraska and Colorado, with similar severities. The optimal solution stablishes a new terminal in Brookings, expands existing terminals in Seattle, Los Angeles, Oakland, St Louis and St Paul and retrofits Billings-Spokane rail link. The Brookings terminal is a backup to accommodate the increase of future demand in more demanding areas of the network. Expanding terminals in Seattle, Los Angeles, Oakland and St Paul as well as retrofitting Billings-Spokane rail link provides more capacity for the alternate route to move east-west freight from the northern part of US rather than the disrupted Midwest part. Expansion of St Louis also provides more capacity for the alternate route passing through South of US.

The optimal design for experiment 6 with strike in Chicago and Los Angeles terminals suggests to open a new terminal in Brookings and expands the Los Angeles, Chicago, Oakland and Kansas City terminals. This provides extra capacity in these terminals in case of strike.

Experiment 7 deals with scenario 7 which considers a terrorist attack in Texas. It affects terminals in Dallas and Houston and three rail links of that state. The optimal design expands the terminal in Houston and retrofits the three disrupted links in that area.

The last experiment (scenario 8) considers the maintenance of Amarillo-Phoenix and Los Angeles-Phoenix rails. The maintenance impacts congestion and capacity reduction in multiple rail links in Texas. Although this scenario is not a natural or human-made disruption, it deals with capacity reduction in a part of network due to inappropriate planning for preventive maintenance. The optimal design suggests that despite building a terminal in Brookings, the five disrupted rail links should be retrofitted to avoid long delays in an important route through the west side of US.

Table 4.4 Experimental results for single scenarios

Experiment #	**Scenario (demand year – disruption scenario)**	**Cost difference between no expansion scenario and experiment dependent expansion** ($)	**Cost difference between nominal scenario expansion and experiment dependent expansion** ($)
0	2040-No disruption	158,104,588	0
1	2040-1	194,538,858	56,350,037
2	2040-2	164,814,523	0
3	2040-3	434,214,619	235,102,514
4	2040-4	137,980,502	49,480,200
5	2040-5	329,777,079	152,963,709
6	2040-6	373,592,268	292,797,864
7	2040-7	188,425,909	53,189,468
8	2020-No disruption	123,276,865	0
9	2020-1	203,866,442	63,880,608
10	2020-2	130,568,534	0
11	2020-3	344,788,771	179,283,058
12	2020-4	91,130,686	32,430,269
13	2020-5	284,051,633	129,664,657
14	2020-6	329,979,654	285,053,957
15	2020-7	151,825,758	27,523,964
16	2025-4	108,040,635	43,145,123
17	2030-6	148,169,117	0
18	2030-3	372,588,044	183,072,192
19	2035-2	152,989,073	0
20	2035-7	390,940,396	315,499,366
21	2040-8	652,125,611	395,066,849

In this work, it is assumed that expanded intermodal terminals can withstand disruptions. However, in reality, there may be situations that are impossible to plan for, such as a labor strike that shut down the entire terminal. From a modeling perspective, these situations can be accounted for by relaxing the resiliency assumption of expanded terminals for specific scenarios and replacing constraint 4.4 with the following constraint for both optimization models.

$$\sum_{w,k} f_k^{ws} \upsilon_{jk}^{w} \le (1-\alpha_j^s)(v_j + v''_{j,l_j} v'_{j,l_j}), \qquad \forall j \in N_3, s \in S \tag{4.16}$$

To better clarify this point, the experiment 6 that involves a labor strike at Los Angeles and Chicago terminals can be considered. As mentioned before, the optimal design with the initial assumption (expanded terminals are able to withstand disruptions) resulted in expansion of Los Angeles, Chicago, Oakland and Kansas City terminals. This result is reasonable because by expanding the terminals in Los Angeles and Chicago they will be able to withstand the impact of disruptions. When the resiliency assumption for expanded terminals is relaxed (i.e. replacing constraint 4.4 with constraint 4.16), it is surmised that there is no benefit in expanding the terminals at Los Angeles and Chicago. Indeed, the optimal design resulted in opening a new terminal in Las Vegas which is in close proximity to Los Angeles and thus can serve as a backup terminal for the Los Angeles terminal. The results indicated that opening a new terminal close to Los Angeles generates more profit than opening a new terminal near Chicago. This is because for the test case more than 80% of the freight shipments have origins or destinations in California.

To understand the need to include both types of risks (demand uncertainty and network disruptions) in the robust decision, consider experiments 3, 11 and 18 with identical disruption scenario “3” but different demand scenarios. The optimal solution indicates that a terminal should be opened at Brookings, OR for all three experiments. However, the expanded terminals differ for each of these three experiments. "Billings", "Houston", "Denver and Billings" are selected for expansion for experiments 3, 11, and 18, respectively. These results validate that the optimal design for each disruption scenario is demand-dependent. Similarly, consider experiments 0 to 8 that have identical demand values but different disruption scenarios. The optimal solution for experiment 0 involves opening two terminals, one at Brookings and one at Fort Smith. The optimal solution for experiment 1 involves opening only one terminal at Brookings and retrofitting "Omaha-Chicago", "Omaha-Billings" and "Chicago-St. Paul" rail links. This is because the full disruption of the rail bridge in Iowa disconnects the route from Omaha to Chicago and the train should reroute to deliver the freight to Chicago. Hence, retrofitting Omaha-Chicago link (which includes replacing the old bridge with a new one) will diminish the chance of further disruptions remarkably. Retrofitting "Omaha-Billings" and "Chicago-St. Paul" (By increasing their capacity) can make them to be an alternate route once the "Omaha-Chicago" connection is disrupted. These results indicate the need to include different demand and disruption scenarios in the network design problem. In other words, the robust solution which considers various demand and disruption scenarios is necessary.

4.5.2.2 EXPERIMENTAL RESULTS FOR ROBUST PROBLEM

Table 4.5 shows the average increase in annual cost savings if all experiments were included in the investment decision rather than only the nominal scenario by utilizing RINEP. Column 1 in Table 4.5 shows the experiment number. Column 2 shows the optimal objective function values of DINEP for each experiment. Columns 3 and 4 show the regret values obtained from solving RINEP in term of cost and percentage for each experiment, respectively. Regret shows the difference between the transportation cost of the experiment under No-expansion, Nominal-expansion and robust expansion and the transportation cost of the experiment with its own optimal expansion design. The results show that the railroad company will incur an average of $73 million (average value of column 3) extra in cost annually for each experiment under the robust design. This average cost difference is almost 35% less on average (compared to average value of column 4 in Table 4.4) compared to the case that considered only the nominal-scenario for expansion decision.

Figure 4.5 depicts regret percentages of each experiment under the cases of No-expansion, expansion considering only the nominal scenario and robust problem includ ing all experiments. It can be seen in Figure 4.5 that out of the 22 experiments, the regret of the robust expansion case is lower than the regret of the No-expansion case for all experiments and lower than the regret of the Nominal-expansion case for 7 experiments. It should be noted that although the regret for Nominal-expansion case is lower compared to the robust expansion case for 70% of experiments, its regret is significantly higher for the remaining 30% of the experiments (e.g. experiments 6, 14, and 20). The benefit of the robust expansion case lies in the fact that it accounts for the worst case scenarios. The average regret/cost ratio of 0.65% for the robust expansion case versus 0.96% for the

Nominal-expansion case confirms the overall advantage of the robust expansion case.

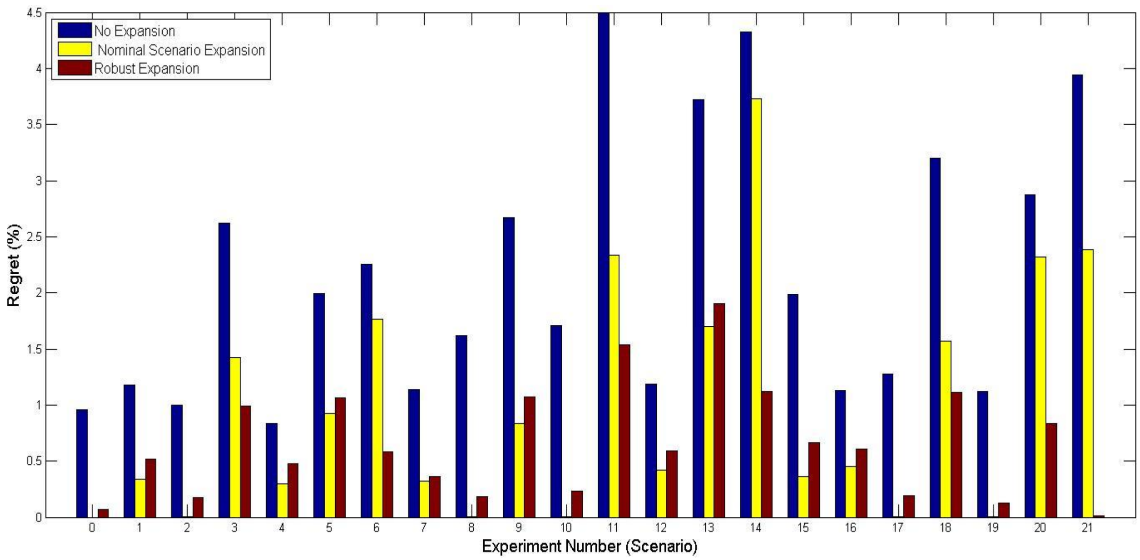


Figure 4.5 Regret for each experiment

The optimal design of the robust problem establishes a new terminal in Brookings. This is a reasonable decision since almost 80% of the freight starts or ends in California. Two terminals in Kansas City and Denver are selected for expansion. Since multiple scenarios are included in the robust problem, the robust solution will work for any scenario. Thus, the expansion of terminals in Kansas City and Denver can compensate the capacity reduction in case of Ice Storm and Tornado scenarios in Midwest. Moreover, those can provide extra capacity for an alternate route passing through Midwest if any scenario happens in North and South of US (southern states are in danger of hurricane and earthquakes are more likely in northwest and west states). The robust problem is more sensitive to worst case scenario. Hence, the final results are more impacted by the worst case scenario which in this case study is experiment 21 with scenario 8 (disruptions happening in Texas and Arizona). The final links chosen for retrofitting verifies this statement. Out of six rail links chosen to be retrofitted in the optimal solution, five of them pass through Texas. Those are Houston-New Orleans, Houston-Amarillo, Dallas-Houston, Phoenix-Amarillo and Dallas-Amarillo. The planner will benefit from this decision in two folds. First, it improves the resiliency of the southern route in case of any disruptions in Southern states, specifically if the worst case scenario happens (scenario 8). Second, this makes the southern route a reliable alternative if any disaster happens in Midwest and Northern states. Chicago-St. Paul is the sixth link in the optimal design to retrofit as 30% of orders start or end in Chicago. This also improves the resiliency of the route ending or staring from Chicago.

Table 4.5 Robust problem results

Experiment #	O_s^* (\$)	**Regret (\$)**	**Regret (%)**
0	16,542,321,527	11,163,213	0.07
1	16,553,001,838	85,842,258	0.52
2	16,550,281,391	29,196,426	0.18
3	16,554,666,496	164,646,494	0.99
4	16,569,423,659	78,826,799	0.48
5	16,557,288,485	176,262,511	1.06
6	16,553,050,966	96,787,324	0.58
7	16,553,016,517	59,947,876	0.36
8	7,620,998,025	14,006,736	0.18
9	7,630,861,372	81,625,026	1.07
10	7,634,230,809	17,966,755	0.24
11	7,668,495,535	117,622,713	1.53
12	7,659,882,813	44,990,212	0.59
13	7,635,051,519	145,639,333	1.91
14	7,634,721,012	85,889,871	1.12
15	7,634,536,576	50,736,989	0.66
16	9,557,474,545	58,282,051	0.61
17	11,616,846,502	22,059,076	0.19
18	11,655,954,662	129,678,603	1.11
19	13,608,715,581	17,730,949	0.13
20	13,609,371,300	113,291,957	0.83
21	16,553,325,372	2,105,791	0.01

To better understand how the network is affected by a single type of disaster instead of a combination of disasters, additional analyses were performed where earthquakes and tornadoes are analyzed separately. Figure 4.6 shows the U.S. earthquake risk map. As shown, California, Washington, and a few of the Midwest states (Tennessee, Missouri, Arkansas and Kentucky) have high risks of earthquakes. Five disruption scenarios with different severities in these three areas are considered to assess the impact to the network due to earthquakes only. Specifically, two scenarios consider earthquakes in California with different severities (moderate and extensive damages), two consider earthquakes in the Midwest (moderate and extensive damages), and one consider extreme earthquakes in Washington and northern part of Oregon. Considering five demand scenarios for each earthquake scenario, the robust problem has a total of 25 experiments. The robust solution for this set of experiments indicate that a new terminal should be established in St. George, Utah and to retrofit three rail links: Memphis-Birmingham, St. Louis-Kansas City, and Memphis-Fort Smith. The result for the location to establish a new terminal is intuitive in that St. George is closest to California (big market) but it is not in a high risk zone. Therefore, this location would be ideal as a backup terminal for the California market; should there be a disruption to terminals in California, this terminal can be used to send or receive shipments from the rest of the U.S. Although terminals in Phoenix and St. Louis are likely to be damaged severely in the event of an earthquake, they are located in smaller markets, and thus, it is more cost-effective to retrofit potentially disrupted rail links in those areas than to establish backup terminals.

Figure 4.7 shows the U.S. tornado risk map. As shown, the Midwest and Southern states are more vulnerable to tornadoes. The tornado region stretches from North Texas to Canada, with the core centers around Oklahoma, Kansas and Northern Texas, as well as Alabama, Mississippi and Tennessee. Three tornado scenarios with different severities are considered. The first scenario considers tornado in the East Tornado Alley, including

Illinois, Kentucky, Tennessee, Alabama and Mississippi. The second scenario expands the previous scenario by including Oklahoma, Arkansas, Nebraska, Missouri and Kansas. The third scenario considers tornadoes in Oklahoma, Arkansas, Nebraska, Missouri, and Kansas.

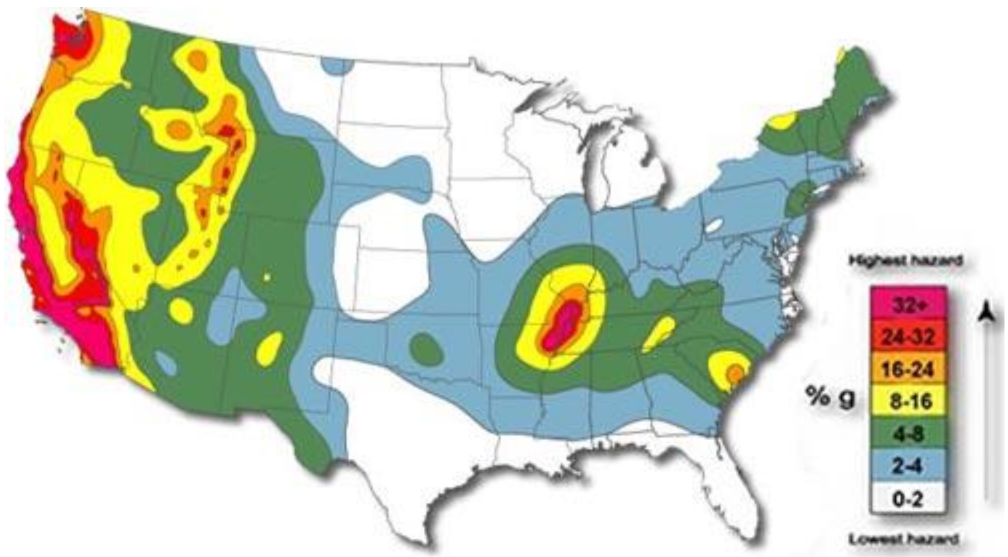


Figure 4.6 Earthquake risk map of US (http://geology.usgs.gov/)

Considering five demand scenarios for each tornado scenario, there is a total of 15 experiments in the robust problem. The robust solution for this set of experiments indicate that a new terminal should be established in Brookings and to retrofit six rail links: Memphis-Birmingham, Memphis-St. Louis, Atlanta-Birmingham, Amarillo-Kansas City, Kansas City-Chicago, and Denver-Omaha. In contrast to the results from the earthquake experiments, among the terminals close to California, Brookings is more desirable because it is furthest away from the tornado region. Similar to the earthquake results, it is more cost-effective to retrofit the aforementioned selected links than to establish backup terminals in the tornado region.

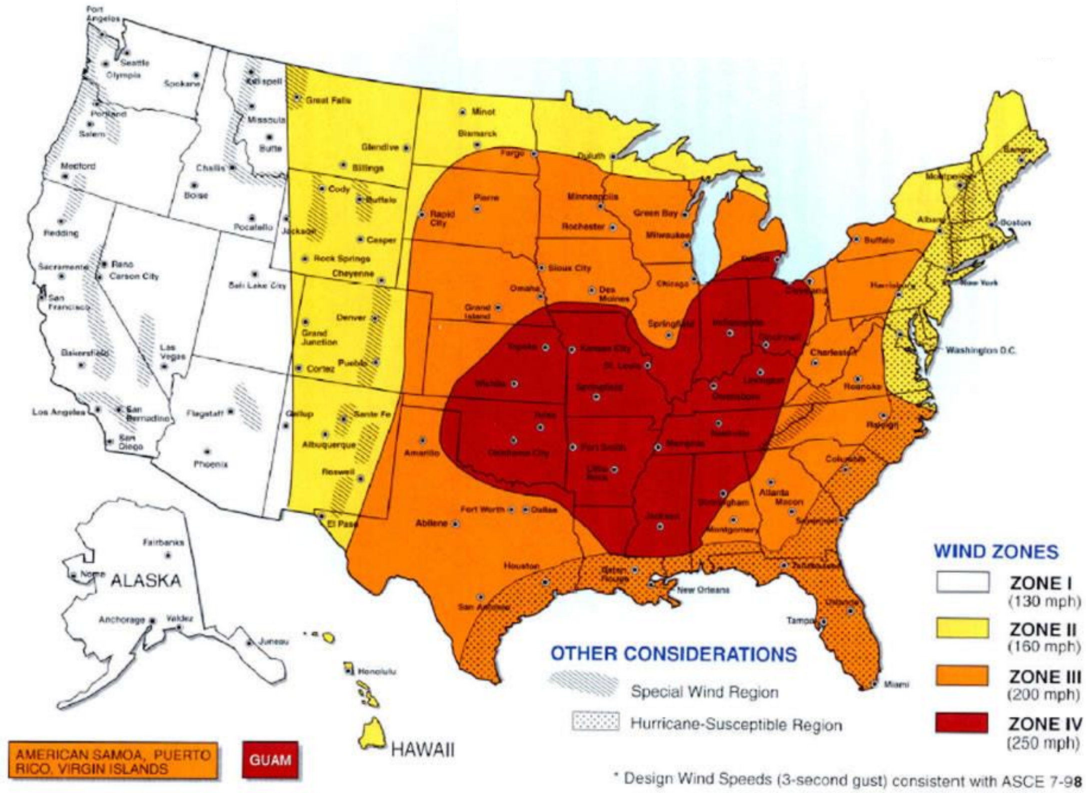


Figure 4.7 Tornado risk map in US (http://strangesounds.org/)

Based on the results on the case study, it can be concluded that rail operators should consider the following guidelines: (1) new terminals should be established close to a large market area which is less likely to be disrupted and be located as far away from the exact location of potential disruption in that area (e.g. position the terminal as far as inland as possible if the market area has the potential to incur a storm surge); (2) within a disrupted area, it is more beneficial to retrofit a high-risk link than to expand an existing terminal (it is counterproductive to expand a terminal that is not accessible by rail whereas a retrofitted link will enable trains to get to an alternate terminal); (3) among the existing terminals, those located close to higher risk areas should be expanded (these expanded terminals can serve as alternate terminals for cargo that are planned to originate or terminate at the disrupted terminals.

It should be noted that our policy recommendations are drawn from the set of scenarios that we examined, and thus, they may or may not reflect the actual operating conditions faced by the railroad operator. However, the developed model can be used to examine other types of scenarios. Moreover, the developed model can be used to perform sensitivity analyses to gain insights into different expansion strategies (e.g. what is the benefit of adding one versus two new terminals to the network).

4.6 CONCLUSIONS

This paper developed a robust and reliable mixed-integer linear model for expanding an intermodal freight network which can cope with fluctuations in demands and disruptions with infrastructure. The model employs a min-max regret approach to identify a network design that is best suited to safe guard against the worst case scenario. A hybrid genetic algorithm which uses column generation to determine the freight flows was developed to solve the proposed model. The proposed algorithm was found to perform well in terms of solution quality and computational time compared against an exhaustive enumeration algorithm for a set of small-sized networks and a larger realistic-size intermodal/highway network in US. The results indicated that it is better (less costly over the long run) to make the extra investments to strengthen the infrastructure than not to. It also indicated that when deciding on the infrastructure strengthening options, it is best to include as many demand and supply scenarios as possible.

This work can be extended by including other modes of transportation and by considering scheduled time tables at intermodal terminals. An additional challenge that could be considered includes utilizing queuing models to account for capacity constraint at intermodal terminals. Lastly, this work can be improved by developing exact algorithms to solve the model.

Long term, this model and its subsequent enhancements could be used by railroad operators as well as transportation planners to identify weak links in the intermodal freight network and to evaluate the capacity of the existing infrastructure. This is particularly important for disaster planning in terms of quantifying the resiliency of the network and improving the network's resiliency and reliability under extreme events. Another aspect of the model that can be improved is to consider explicitly the temporal dimension; that is, consider how the network is affected by the incremental supply and demand changes over time.

CHAPTER 5: A RELIABLE MULTI-PERIOD INTERMODAL FREIGHT NETWORK EXPANSION PROBLEM[3]

[3] Fotuhi, F., and Huynh, N., Submitted to Journal of Computers and Industrial Engineering, 3-14-2017

ABSTRACT

This paper addresses the intermodal freight network expansion problem consisting of multiple periods. In each period, the objective is to determine the locations of new intermodal terminals, the amount of capacity to add to existing terminals, and the existing rail links to retrofit. The multi-period planning problem has the added complexity of determining which period a particular improvement should be made given a limited budget for each time period. A probabilistic robust mathematical model is proposed to address these decisions and uncertainties in the network. Due to the complexity of this model, a hybrid Simulated Annealing (SA) algorithm is proposed to solve the problem and its applicability is demonstrated via two numerical examples. Important managerial insights are drawn and discussed on the benefits of utilizing the multi-period approach.

5.1 INTRODUCTION

An efficient freight transportation system is crucial to the competitiveness of the U.S. in global trade (Ortiz et al., 2007). In the last few decades, tax regulations, green policies (Macharis et al., 2011) and alternative options to move freight at a lower cost have promoted the use of intermodal transportation. Intermodal transportation is defined as movement of goods in the same load units with more than one mode of transport without handling goods themselves while transferring between modes at intermodal terminals (Lin et al., 2014). Around 40% of the total freight volume in U.S. are intermodal shipments. This volume is forecasted to increase 3.25 times by 2040 (Bureau of Transportation Statistics, 2012). To cope with the increasing freight demands and aging infrastructure, intermodal service providers need to continually plan for upgrades of their existing networks, as well as plan for expansion to grow their market share. These expansion plans are long term and are subject to various uncertainties such as changing demands and infrastructure changes. Additionally, the supply capacity of the network may be impacted by natural or man-made disruptions, such as the U.S. West Coast labor dispute in 2002 and damages to oil storage tanks in states of Texas and Louisiana due to hurricane Katrina in 2005 (D' Amico, 2002; Sarkar et al., 2002; Godoy, 2007). Moreover, there are potential new markets which may not have been considered in freight prediction models such as the Freight Analysis Framework (Fotuhi and Huynh, 2015). These factors necessitate the consideration of demand and supply uncertainties in network expansion plans.

One of the principal features of intermodal network design and expansion models is their multi-period nature due to their variable parameters over time (cost, demand, and resources) (Contreras et al., 2011). Additionally, expansion projects require extensive capital investment which may not be available to the stakeholder at the beginning of the planning horizon. These facts are often ignored in the traditional single-period network design problems (Melo et al., 2006). In the multi-period expansion problem, the planning horizon is divided into multiple time periods and the network is incrementally expanded over the planning period, much like how Class 1 railroad companies expand their network over time. Recent examples include CSX building new terminals in Montreal, Pittsburg, and Central Florida. The multi-period approach provides the stakeholder benefits. First, it mitigates the financial burden on the company to acquire significant capital in a short period of time to expand the network. Second, it improves resource management by building terminals "just-in-time," that is, terminals are built only when they are needed. Third and lastly, a more accurate route planning can be done for different time periods utilizing the available resources at that period.

Nagy and Salhi (2007) introduced the concept of multi-period location-routing problems considering different time scales for location and routing decisions. They indicated that a multi-period location-routing framework with shorter routing periods within location decision periods is a better approach to modeling real world location-routing decisions. Their motivation for adopting the multi-period decision problem is the frequent changes in cost and demand over time which significantly impact routing decisions. The same case can be made for intermodal freight network expansion problem. A few studies have addressed the intermodal network expansion problem (Meng and Wang, 2011; Fotuhi and Huynh, 2016); However, to date, there has been only one study that used the multi-period approach for the intermodal network expansion problem (Benedyk et al, 2016). In their study, a new model was proposed to evaluate different expansion scenarios over multiple time periods. Their model finds the optimal location for new terminals, determines the optimal capacities for existing terminals and determines the allocation of origin-destination (OD) demand pairs to terminals. Note that in their model, expansion and allocation decisions are made within the same period regardless of possible disruptions that might happen in the network

The specific objective of this paper is to develop a model for Reliable Multi-Period Intermodal Network Expansion Problem (RMPINEP). An inherent challenge with developing such a model is that expansion and routing decisions are made at different time periods. To model this, it is assumed that the planning horizon is divided into a set of short time periods for routing decisions. However, expansion decisions are made at a subset of these periods and they remain unchanged throughout the planning horizon. It is also assumed that disruptions only happen at expansion time periods and the network recovers from them through the subsequent routing periods until the next expansion period. A robust optimization approach is used to account for forecasted demand errors and possible disruptions during the planning horizon. The contributions of this paper are: (1) development of a new model for multi-period intermodal freight network expansion problem, (2) the developed model considers different time periods for expansion and routing decisions, (3) the developed model incorporates different sources of uncertainty, and (4) development of a meta-heuristic to solve the developed model for large-sized instances.

5.2 LITERATURE REVIEW

Recently, SteadieSeifi et al. (2014) provided a comprehensive review of previous studies in multimodal freight transportation planning classified into strategic, tactical and operational planning levels. Strategic decisions deal with investment in infrastructure which may involve adding and/or maintaining intermodal terminals and network links. The intermodal terminal location problem was first studied by Arnold, Peeters, Thomas and Marchand (2001). They proposed a model to find optimal locations of uncapacitated intermodal terminals in a rail-road intermodal network with unimodal (direct) and intermodal shipping options. In a follow-up work, they improved their previous model by considering intermodal terminals as network arcs to reduce number of decision variables in their model (Arnold et al., 2004). Ishfaq and Sox (2011) formulated a model for finding the optimal locations of intermodal terminals and allocation of commodities with limited time windows to pairs of terminals. Their model ignored the direct shipping option between origins and destinations. Sörensen et al. (2012) added limited capacity at intermodal terminals and direct shipping option to the Ishfaq and Sox (2011) model, but ignored the time window constraints for shipments. Their model was modified by Lin et al. (2014) to reduce redundant variables.

The aforementioned articles assumed there is no uncertainty involved in problem parameters. However, terminal locations are long-term decisions with many uncertainties arising from changes in demand, cost, capacity, and network disruptions. Uncertainty in demand have been widely investigated in network design problems in the last decade. Atamturk and Zhang (2007) proposed a robust two-stage network design model with uncertain demands. The binary link design variables were defined in the first stage and flow was assigned to the network after the actual values of the demand were revealed in the second stage. Yang (2009) formulated a stochastic two-stage air freight hub network design problem. He assumed that the demand is uncertain and varies seasonally. Its model found the optimal number and location of hubs in the first stage and subsequently determined the freight routes in the second stage. Contreras et al. (2011) proposed a model for stochastic uncapacitated hub location problem with uncertain demand and transportation costs. Shahabi and Unnikrishnan (2014) considered uncertain demand within a hub network design problem and showed that more hubs should be opened compared to the deterministic hub network design decisions. Fotuhi and Huynh (2015) were the first to consider uncertain demand for competitive intermodal terminal location problem. They proposed a robust model to find the optimal number, location and size of intermodal terminals and allocation of freight flow to the network for a private rail road company. They showed that terminals that have larger capacities are better equipped in dealing with demand variations.

Capacity is another source of uncertainty which may be caused by natural or human-made disasters in network elements (links or nodes). These disruptions can lead to delay in order delivery, loss of market share, and higher transportation costs. For this reason, it is recommended that capacity be included in models to incorporate reliability in network design decisions (Peng et al., 2011). D'Este and Taylor (2003) suggested that it is best to invest on the weakest elements in the network to reduce network vulnerability to disruptions. Several studies have incorporated disruptions in transportation network design decisions. Rios et al. (2000) formulated a capacitated network design problem with disruptions to network links. Their model determined which set of links to open and their corresponding capacities to guarantee network survival in case of disruptions. Viswanath and Peeta (2003) proposed a multi-commodity maximal covering network design model to address network risks due to earthquakes. Their model identified critical routes in the network and higher risk bridges within those routes that need to be retrofitted. Desai and Sen (2010) considered link failure risk in a reliable network design model which allocated resources to mitigate the disruption impacts on higher risk links in the network. Peeta et al. (2010) formulated an investment model to retrofit higher risk links in a highway network. A few studies have incorporated facility (node) disruptions in logistics and transportation network design problems. Peng et al. (2011) proposed a model for reliable logistics network design problem with disruption risk at suppliers and distribution centers. Their model found optimal locations for these facilities and flow allocation to the corresponding network minimizing disruption risks. An et al. (2011) considered disruptions in transshipment nodes for a hub-and-spoke network design problem. Their model found the optimal locations of backup hubs while minimizing the expected transportation cost for normal and disrupted situations. Marufuzzaman et al. (2014) incorporated disruptions at intermodal terminals in a biofuel supply chain design problem. Their model found locations of intermodal terminals and bio-refineries while minimizing total fixed and transportation costs. Miller-Hooks et al. (2012) considered disruptions in both network links and terminals of an intermodal network design problem. They found best recovery and pre-disaster policies to maximize network resiliency against disruptions. Fotuhi and Huynh (2016) proposed a model for intermodal network expansion problem considering link and terminal failures. They also included uncertain demand in their expansion and routing decisions as well. Their model found optimal locations of new intermodal terminals, existing terminals to expand and less resilient links of the network to retrofit to increase network resiliency to disruptions.

One of the main characteristics of network design models which have been neglected in the aforementioned studies is their dynamic nature (i.e., multi-period planning). The literature on multi-period transportation network design is scarce. Contreras et al. (2011) were the first to model a multi-period hub location problem. Their model identified when and where to open new hubs and to close open hubs as well as flow assignment to pairs of open hubs. They assumed that the flow fluctuates over time. Taghipourian et al. (2012) employed the concept of multi-period planning for a virtual hub network design problem of airline industries. They also assumed that hubs are uncapcitated and hubs opened in one period might be closed in later periods. Recently, Gelareh et al. (2015) developed an uncapacitated multi-period hub location model for a liner shipping provider. They assumed that the service provider will lease one hub in a period and will end the lease in another period. The objective of their model is to determine when to lease a new hub and when to end the lease for an operating hub. They considered a limited budget available to lease new hubs and operation of existing hubs in the system for each period. Alumur et al. (2015) formulated multi-period single and multiple-allocation hub location problems with limited capacities at hubs. The objective of their model is to determine when and where to locate a new hub and which open hubs to expand to minimize total construction, expansion and routing costs. They assumed that once a hub is opened in a period it will remain open throughout the entire planning horizon. In a recent work, Benedyk et al. (2016) proposed a location-allocation model for intermodal network expansion problem over multiple time periods with uncertain demands. They considered new intermodal terminals to add to the network and expanding existing terminals. They demonstrated their model on a sample freight network within the U.S. and evaluated a few expansion scenarios on a 10-year planning horizon. Their model found optimal allocation of shippers and receivers to transfer points (intermodal terminals and ports) but did not find specific routes for them.

This work extends the work of Fotuhi and Huynh (2016) and incorporates the multi-period planning approach proposed by Benedyk et al. (2016) for intermodal freight networks. It also incorporates the idea from Albareda-Sambola et al. (2012) of considering different routing and design time scales. To the best of the authors' knowledge, this is the first work in intermodal freight network expansion that considers multi-period planning with different time scales for expansion and routing decisions and considering demand and supply uncertainties.

5.3 PROBLEM STATEMENT

RMPINEP is a network expansion problem of an existing rail-road intermodal network with a finite planning horizon, uncertain demand and disruption risk at network terminals and links. Commodities are delivered to the customers using intermodal option via a set of intermodal terminals or directly with trucks. The network features N_1, sets of existing terminals, N_2, sets of candidate nodes for installing new terminals, A_1, sets of highway links, and A_2, sets of rail links. The planning horizon is divided into T time periods (years, quarters of years). As mentioned before, two different time scales are considered for routing and expansion decisions. While routing decisions are made at each time $t \in T$, a T_I subset of time periods of the planning horizon, $T_I \subset T$, are selected for strategic expansion decisions. At each period $t \in T$, the demand for W_t sets of Origin-Destination (OD) pairs selected from N_3, sets of highway nodes (cities) is routed through the network. K_w^t is the set of paths for OD pair $w \in W_t$ at routing period $t \in T$.

This work considers the following assumptions:

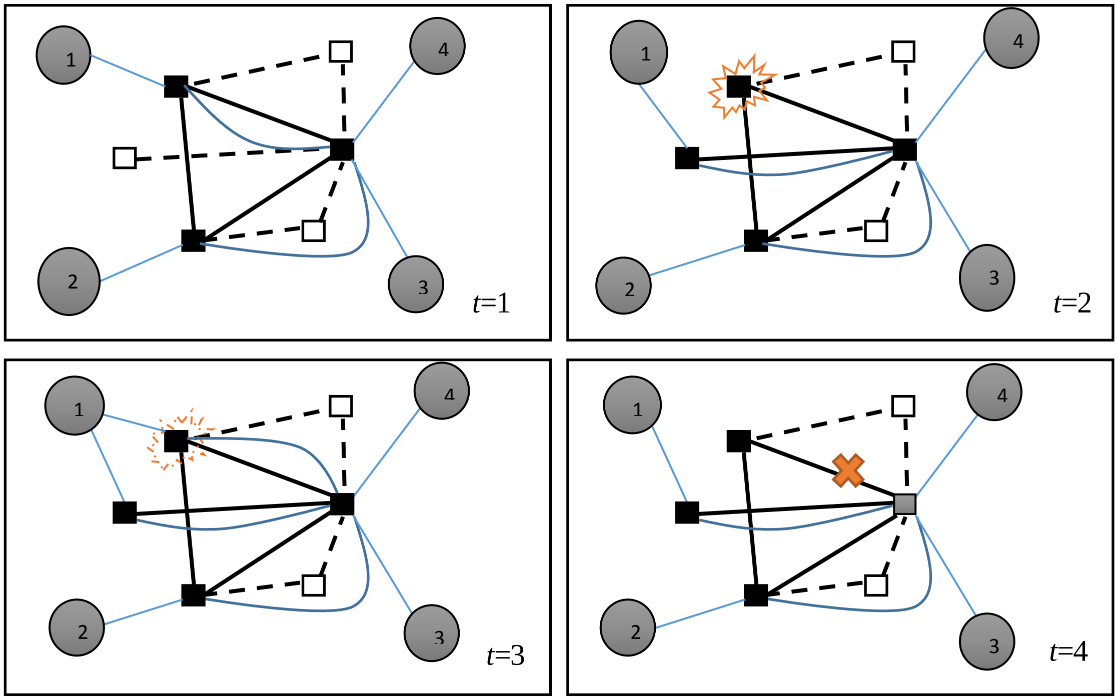
- Terminals opened at each expansion period stay opened through the planning horizon.
- Capacity of expanded terminals is not reduced through the planning horizon.
- Transfer time and cost are only considered for terminals that the shipment changes mode.
- It is assumed that capacity modules with different sizes are available for each existing terminal. At each expansion period, at most one capacity module can be selected from a predefined set of capacity modules. $L_j^{t'}$ is the set of capacity modules for terminal $j \in N_1$ at expansion period $t' \in T_I$.
- A penalty cost is considered for shipments violating delivery time windows.
- OD pairs pattern and their corresponding flows change during the planning horizon.
- There is a limited budget $B_{t'}$ for expansion decisions at each expansion period $t' \in T_I$.

- Expansion and routing decisions are affected by a set of disruption and demand scenarios, $S_{t'}$ for each expansion period $t' \in T_I$ and its underlying routing periods. It is assumed that disruption damages decrease through the routing sub-periods of an expansion period.

The optimal decision seeks to find when and where to open new intermodal terminals, when to expand an existing intermodal terminal and its optimal capacity module, and retrofitting priority of higher risk links in each expansion period as well as routing of freight flow at each routing period minimizing total expansion costs and expected routing costs over all scenarios.

5.3.1 ILLUSTRATIVE EXAMPLE

Figure 5.1 depicts a sample solution of RMPINEP. The network has 3 existing terminals, 3 rail links, 3 candidate terminals, 4 cities, 2 OD pairs (1-3,2-4), 4 time periods and $T_I = \{2,4\}$. Blue lines show the optimal routes for each OD pair. As illustrated in fig. 1, one terminal is fully disrupted at *t*=2. Hence the demand for OD pair (1-3) is rerouted by utilizing a new terminal which is opened at this period. Time 3 is a routing period and the disrupted terminal is partially recovered. Accordingly, the demand for OD pair (1-3) is partially met by the disrupted terminal. At *t*=4, the demand for OD pair (1-3) is increased and one link in one of its optimal routes in the previous period is out of operation. However, one terminal in the other route is expanded to fully meet the demand for this OD.



□: Candidate terminals; ■: Existing terminals; —— : Existing rail links; - - : Candidate rail links

●: Cities (Origins/Destinations); ■: Expanded terminals; : Disruption at terminals; : Disruption at links

Figure 5.1 A sample solution of the problem.

5.4 MATHEMATICAL MODEL

A robust path-based mixed integer model is proposed for RMPINEP. Model parameters and notations are mentioned as follows:

<u>Parameters</u>

t_a: Average travel time on link $a \in (A_1 \cup A_2)$

τ_j: Average transfer time at terminal $j \in (N_1 \cup N_2)$

$T_w^{st'}$: Time window for OD pair $w \in W_t$ under scenario s at expansion period $t' \in T_I$

$F_j^{t'}$: Annual fixed cost of opening candidate terminal $j \in N_2$ at expansion period $t' \in T_I$

c_a^t: Travel cost per unit of flow on link $a \in (A_1 \cup A_2)$ at routing period $t \in T$

$c_j'^t$: Transfer cost at terminal $j \in (N_1 \cup N_2)$ per unit of flow at routing period $t \in T$

$C_j^{l_j^{t'}}$: Capacity expansion cost for module $l_j^{t'} \in L_j^{t'}$ at terminal $j \in N_1$

v_j: Current capacity of existing terminal and capacity of new terminals $j \in (N_1 \cup N_2)$

e_a: Capacity of link $a \in (A_1 \cup A_2)$

$d_w^{s_{t'}t}$: Demand of OD pair $w \in W_t$ under scenario $s_{t'} \in S_{t'}$ at routing period $t \in T$

$\alpha_j^{s_{t'}t}$: Disruption percentage of terminal $j \in (N_1 \cup N_2)$ under scenario $s_{t'}$ at routing period $t \in T$

$\beta_a^{s_{t'}t}$: Disruption percentage of link $a \in (A_1 \cup A_2)$ under scenario $s_{t'}$ at routing period $t \in T$

$h_a^{t'}$: Hardening cost of link $a \in A_2$ at expansion period $t' \in T_I$

$\theta_{s_{t'}}$: If expanded terminals withstand disruptions under scenario $s_{t'} \in S_{t'}$

$\sigma_{s_{t'}}$: If retrofitted rail links withstand disruptions under scenario $s_{t'} \in S_{t'}$

$p_{s_{t'}}$: Probability of occurrence of scenario $s_{t'} \in S_{t'}$ at expansion period $t' \in T_I$

$\delta_{akt}^{ws_{t'}}$: path-arc incidence (= 1 if link $a \in (A_1 \cup A_2)$ is used in path k for OD pair $w \in W_t$ under scenario $s_{t'} \in S_{t'}$ at routing period $t \in T$; 0 otherwise)

$\upsilon_{jkt}^{ws_{t'}}$: path-terminal incidence (=1 if shipments change mode at terminal $j \in (N_1 \cup N_2)$ in path k for OD pair $w \in W_t$ under scenario $s_{t'} \in S_{t'}$ at routing period $t \in T$; 0 otherwise)

RMPINEP encompasses strategic (expansion) and operational (routing) decision variables. Once strategic decision variables are determined at each expansion period, routing decision variables are found for subsequent routing periods. The decision variables are as follows:

Decision Variables

$y_j^{t'}$: 1, if a terminal is opened at node $j \in N_2$ at expansion period $t' \in T_I$; 0, otherwise

$v'^{t'}_{j,l_j^{t'}}$: 1, if expansion design $l_j^{t'}$ is selected for terminal $j \in N_1$ at expansion period $t' \in T_I$; 0, otherwise

$z_a^{t'}$: 1, If link $a \in A_2$ is hardened at expansion period $t' \in T_I$;0, otherwise

$x_{kt}^{ws_{t'}}$: 1, if a shipment for OD pair $w \in W_t$ uses path k under scenario $s_{t'} \in S_{t'}$ at routing period $t \in T$

$f_{kt}^{ws_{t'}}$: Amount of freight flow for OD pair $w \in W_t$ on path k under scenario $s_{t'} \in S_{t'}$ at routing period $t \in T$

Using the aforementioned variables and parameters, RMPINEP is formulated as follows:

$$Min \sum_{j \in N_2, t' \subset T} F_j^{t'} y_j^{t'} + \sum_{j \in N_1, t' \subset T} v'^{t'}_{j,l_j} C_{j,l_j} + \sum_{a \in A_2, t' \subset T} z_a^{t'} h_a^{t'} + p_{s_{t'}} \sum_{k,w,s,t \in T} f_{kt}^{ws_{t'}} c_k^t \tag{5-1}$$

Subject to:

$$\sum_{w,k} f_{kt}^{ws_{t'}} \upsilon_{jkt}^{ws_{t'}} \leq \theta_{s_{t'}} [(1-\alpha_j^{s_{t'}t}) v_j + \sum_{t'' \leq t'} v''_{j,l_j} v'^{t'}_{j,l_j}], \qquad \forall j \in N_1, s_{t'} \in S_{t'}, t \in T, t' \subset T \tag{5-2}$$

$$\sum_{w,k} f_{kt}^{ws_{t'}} \upsilon_{jkt}^{ws_{t'}} \leq (1-\theta_{s_{t'}})(1-\alpha_j^{s_{t'}t})(v_j + \sum_{t'' \leq t'} v''_{j,l_j} v'^{t'}_{j,l_j}), \qquad \forall j \in N_1, s_{t'} \in S_{t'}, t \in T \tag{5-3}$$

$$\sum_{w,k} f_{kt}^{ws} \upsilon_{jkt}^{ws_{t'}} \leq v_j, \qquad \forall j \in N_2, s_{t'} \in S_{t'}, t \in T \tag{5-4}$$

$$\sum_{j \in N_2} F_j^{t'} y_j^{t'} + \sum_{j \in N_1} v'^{t'}_{j,l_j} C_{j,l_j} + \sum_{a \in A_2} z_a^{t'} h_a^{t'} \leq B_{t'}, \ \forall t' \subset \mathrm{T} \tag{5-5}$$

$$\sum_{l_j} v'^{t'}_{j,l_j} \leq 1, \qquad \forall j \in N_1, \forall t' \subset T \tag{5-6}$$

$$\sum_{w,k} f_{kt}^{ws_{t'}} \delta_{akt}^{ws_{t'}} \leq (1-\beta_a^{s_{t'}t}) e_a, \qquad \forall a \in A_1, s_{t'} \in S_{t'}, t \in T \tag{5-7}$$

$$\sum_{w,k} f_{kt}^{ws_{t'}} \delta_{akt}^{ws_{t'}} \leq \sigma_{s_{t'}} (1-\beta_a^{s_{t'}t} (1-\sum_{t''\leq t'} z_a^{t''}))e_a, \quad \forall a \in A_2, s_{t'} \in S_{t'}, t \in T \tag{5-8}$$

$$\sum_{w,k} f_{kt}^{ws_{t'}} \delta_{ak}^{wt} \leq (1-\sigma_{s_{t'}})(1-\beta_a^{s_{t'}t})e_a, \quad \forall a \in A_2, s_{t'} \in S_{t'}, t \in T \tag{5-9}$$

$$\begin{aligned} &\sum_{a\in A_1}(1+\beta_a^{s_{t'}t})t_a\delta_{ak}^{wt} + \sum_{a\in A_2}(1+\beta_a^{s_{t'}t}(1-\sum_{t''\leq t'} z_a^{t''}))t_a\delta_{ak}^{wt} + \sum_{j\in N_1}(1+\alpha_j^{s_{t'}t})(\tau_j \upsilon_{jk}^{wt}) + \sum_{j\in N2}\tau_j \upsilon_{jk}^{wt} \\ &\leq T_w^{s_{t'}t} + M(1-x_{kt}^{ws_{t'}}), \quad \forall w \in W, k \in K_w^t, s_{t'} \in S_{t'}, t \in T \end{aligned} \tag{5-10}$$

$$f_{kt}^{ws_{t'}} \leq Mx_{kt}^{ws_{t'}}, \quad \forall k \in K_w, w \in W, s_{t'} \in S_{t'}, t \in T \tag{5-11}$$

$$\sum_{w,k} x_{kt}^{ws_{t'}} \upsilon_{jkt}^{ws_{t'}} \leq M \sum_{t'} y_j^{t'}, \quad \forall j \in N_2, s_{t'} \in S_{t'} \tag{5-12}$$

$$\sum_{k} f_{kt}^{ws_{t'}} = d_{wt}^{s_{t'}t}, \quad w \in W_t, s_{t'} \in S_{t'}, t \in T \tag{5-13}$$

$$\sum_{t'\subset T} y_j^{t'} \leq 1, \quad \forall j \in N_2 \tag{5-14}$$

$$\sum_{t'\subset T} z_a^{\ddot{t}'} \leq 1, \quad \forall a \in A_2 \tag{5-15}$$

$$y_j^{t'}, z_a^{t'}, v_{j,l_j}^{'}, x_{kt}^{ws_{t'}} \in \{0,1\}, f_{kt}^{ws_{t'}} \geq 0, \forall w \in W_t, a \in A_2, j \in N_2, s_{t'} \in S_{t'} \tag{5-16}$$

Objective function (5-1) minimizes total expansion cost and expected routing cost over all scenarios and routing periods. Constraints (5-2) and (5-3) ensure that capacity of existing terminals are not violated for all routing periods. If expanded terminals stay resilient under a specific scenario at later periods, constraints (5-2) are activated. Otherwise, Constraints (5-3) are utilized. Constraints (5-4) guarantee that capacity of new terminals are not violated for all routing periods. Constraints (5-5) limit expansion decisions by the available budget at each expansion period. Constraints (5-6) ensure that at most one capacity module can be selected for existing terminals. Constraints (5-7) prohibits capacity violation of highway links. Constraints (5-8) and (5-9) guarantee that capacity of rail links are not violated. Like the assumption for constraints (5-2) and (5-3), constraints (5-8) are activated if hardened links stay resilient in case of disruptions and constraints (5-9) are activated in the opposite case. Constraints (5-10) ensure that time windows are not violated. Constraints (5-11) and (5-12) assure that freight flow are assigned to open terminals. Constraints (5-13) guarantees that all demand is met for each OD pair. Due to capacity limitations and time windows, such an assumption is not realistic. Hence, unmet demand for each OD pair is considered as the amount of flow over a hypothetical path between origin and destination of an OD pair with a penalty cost. Constraints (5-14) ensure that a candidate node can be opened at most once over all expansion periods. Similarly, constraints (5-15) guarantee that each rail link is retrofitted at most once over the planning horizon. Constraints (5-16) are the integrality of decision variables.

5.5 SOLUTION METHOD

RMPINEP reduces to the discrete network design problem when considering single period with no uncertainty in parameters. Since the discrete network design problem is *NP*-hard (Meng and Wang, 2011), RMPINEP is *NP*-hard as well. This problem is computationally intractable due to the following reasons. First, $(|T_I|+1)^*|N_2|^*|N_1 * L_{j\in N_1}|^*|A_2|$ possible configurations of strategic decision variables should be examined for optimal decision. Although budget constraint limits this number, a remarkable set of configurations stay feasible for evaluation. On the other hand, there is a huge number of possible paths for each OD pair. It is difficult and computationally expensive to enumerate all of them for each configuration involving multiple scenarios and their corresponding routing periods. Traditional optimization solvers are not able to solve this problem even for very small networks due to the huge number of variables and constraint. Hence, a hybrid Simulated

Annealing (SA) algorithm integrated with Column Generation (CG) for routing decisions is proposed to solve the problem. SA finds optimal values for strategic decision variables. Once these variables are determined, CG is used to find freight flow assignment for each routing period under each scenario.

SA was inspired by the annealing process in metals. The metal is heated to a high temperature and is gradually cooled down to attain to its optimal shape. Molecules can move freely in high temperatures but they are stuck in lower temperatures. SA, a probabilistic search algorithm, starts with an initial solution at a high temperature and explores the nearby solutions. If the neighbor solution is better, then it is accepted as the current solution. Otherwise, the algorithm accepts a worse solution with a probability. As it cools down, this probability becomes lower. The idea of accepting a non-improving solution is to escape from local optima. A complete overview of the algorithm can be found in Kirkpatrick et al. (1983).

5.5.1 SOLUTION REPRESENTATION

The feasible strategic solutions are coded as integer single dimensional arrays. Each array consists of two sections for new terminal location and link retrofitting decisions and $|T_I|$ sections for capacity expansion of existing terminals. Figure 5.2 depicts a sample representation of a solution considering a network with 3 existing terminals, 2 candidate terminals, 4 links and 2 expansion periods. As shown, candidate terminal 1 never opens through the planning horizon while candidate terminal 2 will be opened at period 1. Links 1 and 3 are not retrofitted while links 2 and 4 are retrofitted at periods 2 and 1, respectively. In expansion period T_1, capacity module 1 is selected for existing terminal 1. Existing terminals 2 and 3 are not expanded at this period. Capacity modules 1 and 2 are selected for existing terminals 2 and 3 at time T_2, respectively. Existing terminal 1 is not expanded at this period. Each configuration is checked to avoid budget violation. The algorithm generates a random initial solution and checks its feasibility regarding budget constraint. Once the strategic variables are fixed, RMPINEP reduces to the Capacitated Multi-Commodity Intermodal Network Flow Problem with Time Windows (CMINFPT), one for each routing period and scenario. The CG algorithm embedded with an intermodal label setting algorithm proposed by Fotuhi and Huynh (2016) is used to assign freight flow to the network. The objective function is computed once routing subproblems are solved.

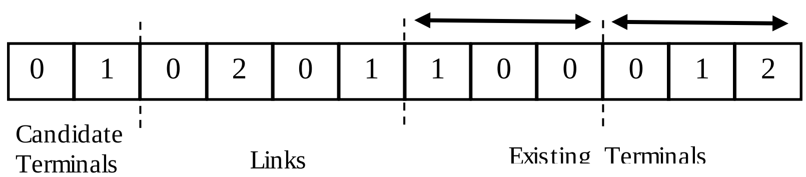


Figure 5.2 A sample representation of a solution.

5.5.2 NEIGHBORHOOD SEARCH MECHANISM

For each solution, a neighboring solution is generated as follows:

Step 1: Select a random strategic variable (candidate terminal, link or existing terminal), xx and a random period, tt.

Step 2: If xx is a candidate terminal,

If the corresponding value of xx equals tt,

Fixed-cost/capacity ratio (F^{tt}/v) is computed for candidate terminals which are not opened at tt. Terminal with lowest ratio is opened at tt and xx is closed for the whole planning horizon. If there is no terminal opened at other time periods, xx is closed and no terminal is selected to open at tt.

Else,

Fixed-cost/capacity ratio (F^{tt}/v) is computed for candidate terminals opened at tt. Terminal with highest ratio is closed for the whole planning horizon and xx is opened at tt. If there is no new terminal at tt, xx will be opened at this time period.

Else if xx is an existing terminal,

Two options are available for neighborhood search:

1. Randomly change the capacity module of xx at time tt to a different one from its available modules.
2. Swap the capacity modules of xx and a random existing terminal, yy, at tt. Modules can be exchanged if they are within the maximum number of eligible modules of the alternate terminal at tt.

Else,

If the corresponding value of xx equals tt,

Harden-cost/capacity ratio (h^{tt}/e) is computed for links which are not retrofitted at tt. Link with lowest ratio is retrofitted at tt and xx is not maintained for the whole planning horizon. If there is no link which is retrofitted at other time periods, xx is not maintained and no link is selected for maintenance at tt.

Else,

Harden-cost/capacity ratio (h^{tt}/e) is computed for retrofitted links at tt. Link with highest ratio is not retrofitted for the whole planning horizon and xx is retrofitted at tt. If there is no retrofitted link at tt, xx will be retrofitted at this period.

Step 3: Check the budget constraint for the new configuration. If the configuration is not feasible, discard it and go to step 1.

5.5.3 EVALUATE THE NEIGHBORING SOLUTION

Once a feasible neighboring solution is generated, freight flow is assigned to the network for all routing periods and the objective function value ($C(\lambda)$) of this configuration is computed. If $C(\lambda) <= C(\lambda^0)$, $C(\lambda^0)$ is the objective function of the current solution, the new configuration is accepted as the current solution and $C(\lambda^0)=C(\lambda)$. Otherwise, the probability of accepting this non-improving solution is determined by Boltzman function $e^{-\Delta/\psi}$. Δ is the difference between $C(\lambda^0)$ and $C(\lambda)$ and ψ is the current temperature. A random number $\partial \in [0,1]$ is generated. The inferior neighboring solution is accepted if $\partial \le e^{-\Delta/\psi}$. Otherwise the current solution stays the same. If $C(\lambda)$ is smaller than $C(\lambda^*)$, the best solution found so far, $C(\lambda^*)=C(\lambda)$.

5.5.4 COOLING SCHEDULE

A predefined number of solutions *K*, known as neighborhood size, are generated and evaluated at each temperature. The temperature is decreased with the following function after *k* neighboring solutions are evaluated.

$$\psi_{i+1} = \Omega * \psi_i$$

Where $\Omega \in (0,1)$ is the cooling rate by which the temperature is decreased. The algorithm terminates if $\psi_i \le \psi_0$, ψ_0 is the frozen temperature. It may also terminate if the solution is not improved for a predefined number of iterations.

5.6 COMPUTATIONAL EXPERIMENTS

The proposed solution algorithm is coded in MATLAB R2016 and all experiments are run on a desktop computer with an Intel Core 2 Duo 2.66 GHz processor and 24 GB of RAM.

A random small network is used to validate the proposed model and algorithm in terms of optimality and computational time. The application of the model on real-sized network is also investigated.

5.6.1 SMALL SIZE NETWORK

A small hypothetical network with 10 cities, 3 existing terminals, 4 candidate terminals, 10 periods including 2 expansion periods and 10 routing periods (10 years) is considered. Expansion decisions are made at periods 1 and 6 with 4 and 3 scenarios respectively. At each routing period, 6 to 10 random OD pairs are selected from the cities. Figure 5.3 illustrates the network. It is assumed that with 85% chance, no disruption happens at the first expansion period but there is a 5% chance of disruption at existing terminal 3 and all links connected to it, 5% chance of disruption at existing terminal 1 and all its inbound and outbound links and a 5% chance of disruptions at all outbound links from city 2. The second expansion period faces 90% chance of no disruption, 5% chance of disruption at terminal 2 and all links connected to it and 5% chance of disruption at outbound links from cities 1 and 3. Table 5.1 presents the problem parameters considered for the small hypothetical network.

This example is solved with both SA and Exhaustive Enumeration (EE). SA could find the optimal solution in 1 hour while it took the EE more than one day to find the optimal solution. The optimal solution involves opening candidate terminals 4 and 2 at the first and second expansion periods, respectively. Figure 5.4 illustrates the impact of multi-period planning on routing decisions. Specifically, it shows the routing results of one of OD pairs (1-10) under the second expansion period for the second scenario.

Table 5.1 parameters of small hypothetical network

Parameter	Value
Travel cost on highway links	Uniform(2,4)
Travel cost on rail links	Uniform(0.1,1.1)
Transfer cost at intermodal terminals	Uniform(2,3)
Travel time on highway links	Uniform(1,3)
Travel time on rail links	Uniform(5,10)
Transfer time at intermodal terminals	Uniform(10,30)
Capacity of highway links	Uniform(1000,3000)
Capacity of rail links	Uniform(10000,20000)
Capacity of intermodal terminals	Uniform(30000,50000)
Fixed cost of opening new terminals	Uniform(500000,1000000)
Cost of retrofitting links	Uniform(300000,400000)
Cost of expanding existing terminals	Uniform(200000,300000)

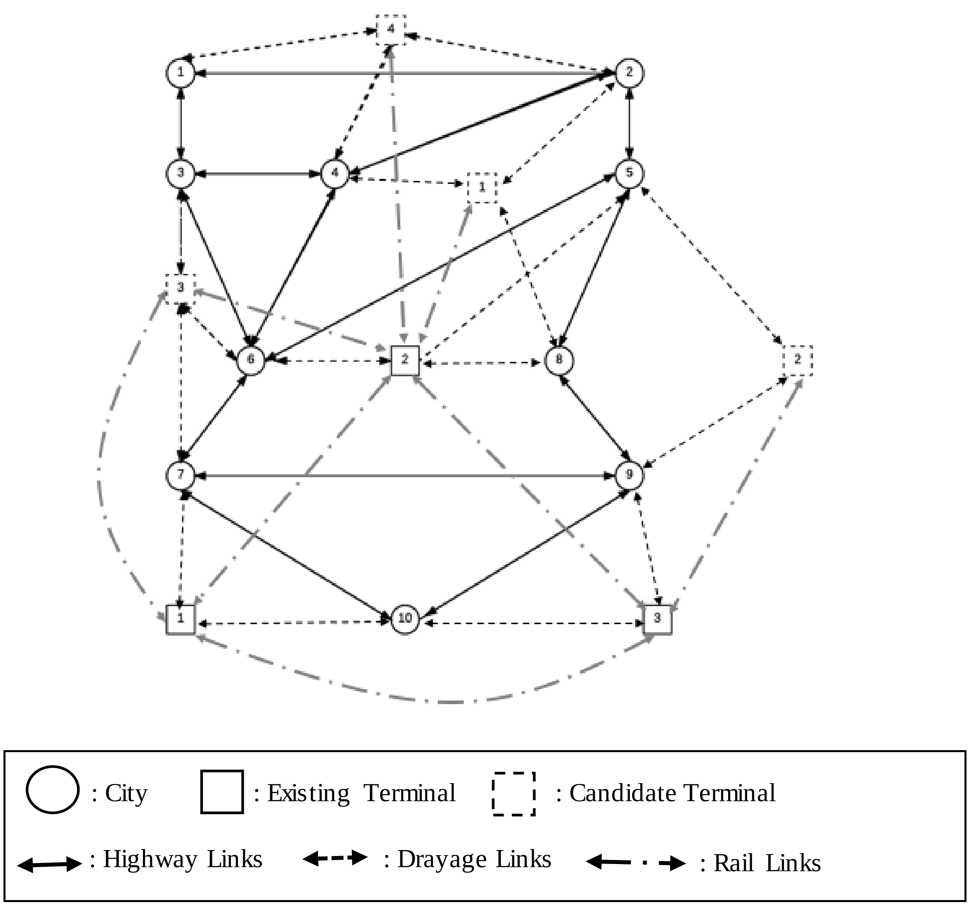
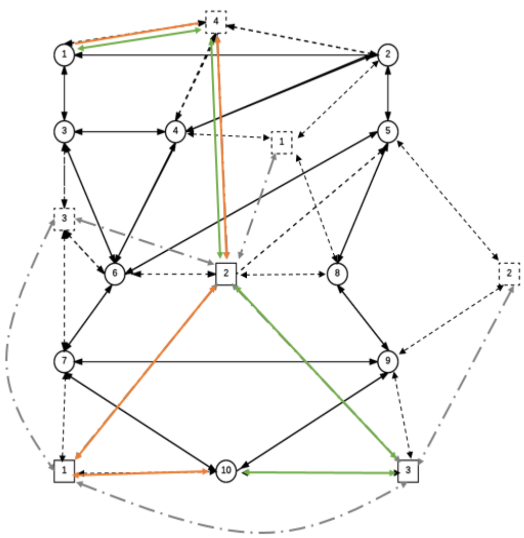
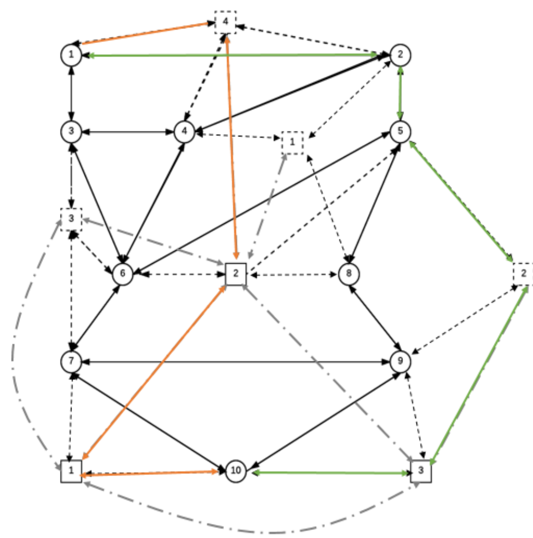


Figure 5.3 Network of the small case study.

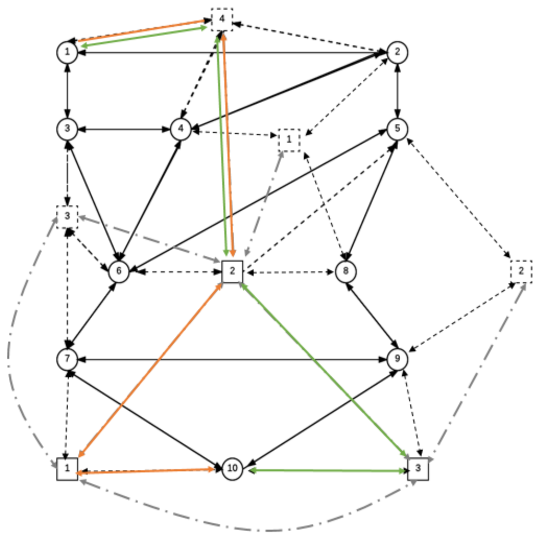
As shown in Figure 5.4, four different paths are selected for this OD pair through the routing subperiods. Routing periods 1, 3 and 4 have the same set of routes while periods 2 and 5 have one route in common with the other three routing periods. The orange route which is selected for all periods is the shortest path for this OD pair. However, due to limited capacity, the flow is partially covered by this route and the rest is moved via alternative routes. Different set of routes for different routing periods verify the initial theory of considering shorter routing periods within expansion periods because the variable demand, cost and capacities can significantly impact routing decisions which cannot be accounted for in traditional single-period models.



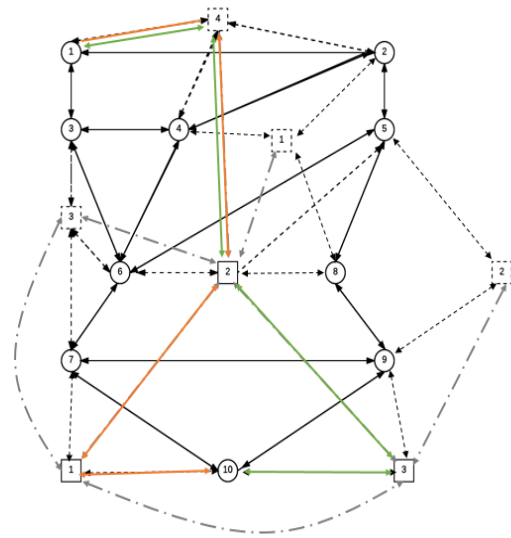
Routing Period 1



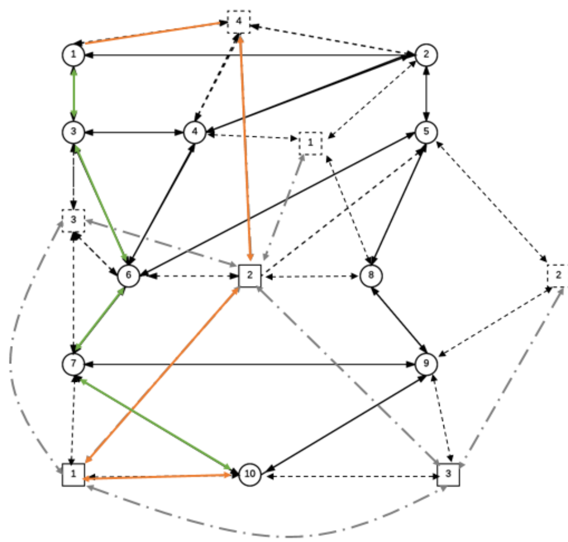
Routing Period 2



Routing Period 3



Routing Period 4



Routing Period 5

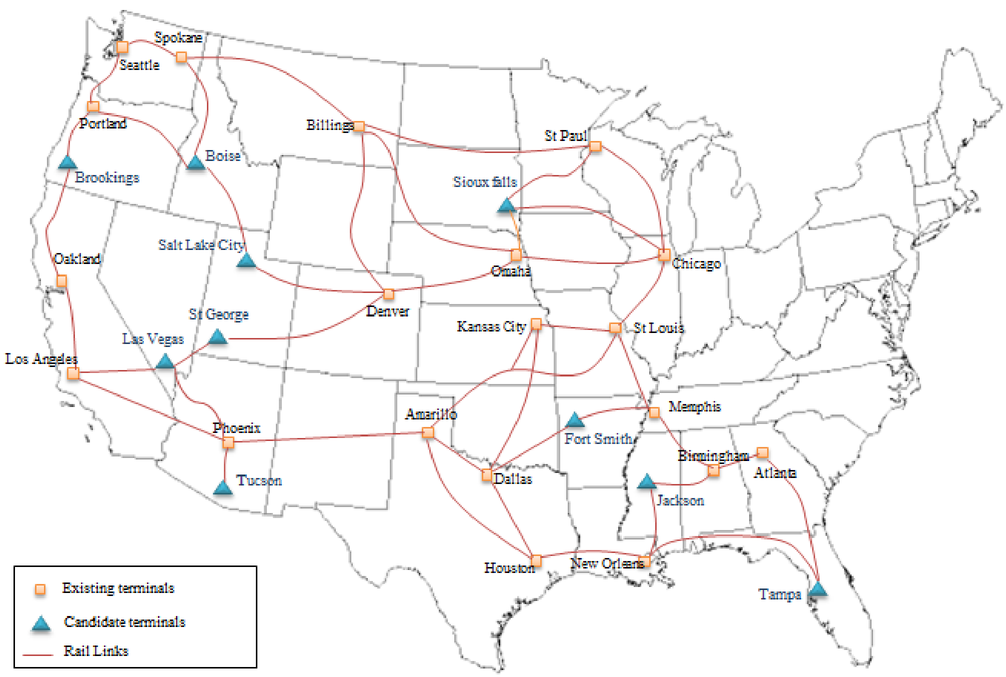
Figure 5.4 routing results of one OD pair under all outing subperiods of one expansion period for small case study.

To demonstrate the benefits of utilizing the multi-period approach to make network expansion decisions, a comparison is made against the single-period approach which involves only one expansion and routing period. The single-period model is solved considering all OD pairs for different periods of the original problem and assumed the worst case scenario: highest demand and smallest time windows for corresponding OD pairs. It also considers the highest disruption percentages for links and terminals for all scenarios. The reason behind this approach is to emulate a manager's decision to expand the network to accommodate the worst case scenario within the planning period. The budget for the single-period model is the sum of the budget of all expansion periods of the original problem. The solution to the optimal single-period model involves opening two new terminals at candidate nodes 2 and 3 at the beginning of the planning horizon. Candidate terminal 2 is also selected under the multi-period case; however, it will not be opened until the second expansion period. The multi-period approach outperforms the single-period one in three folds. It reduces the total routing cost by 18%, increases capacity utilization by 5%, and reduces lost demand by 15% for the entire planning horizon. Note that the multi-period model also has the advantage of not presuming that the entire budget is available at the beginning of the planning horizon. Accordingly, the multi-period version of network expansion is more efficient in terms of overall cost, budget availability and resource utilization.

5.6.2 LARGE SIZE NETWORK

In this section, RMPINEP is applied to a realistic-sized intermodal network of a railroad company in U.S. As shown in previous section, this problem is computationally too expensive for even small size networks with EE thus this large size network in only solved with SA.

The network consists of a rail network of a class 1 railroad company with 20 existing terminals which covers Midwest and Western side of the U.S. It also includes a highway network of 44 major cities in the same geographic area with interstates between them. The company decides to increase its operational capacity by opening new terminals from 10 candidate nodes, expanding its existing terminals and retroffiting weaker rail links in its network. Candidate terminals are in a good proximity of areas with higher demand quantities and disruptions risks. Selected terminals can serve as back up terminals in case of disruptions and fluctuations in the demand. Figures 5.5(a) and 5.5(b) depict the aforementioned rail and highway networks, respectively.



(a)

(b)

Figure 5.5 Test case network: (a) Intermodal rail network; (b) Highway network.

Highway distances and their corresponding travel times were drawn from Google Maps. Railroad company's website provided rail mile distances between intermodal terminals. Travel times on rail links were computed by assuming an average speed of 35 miles per hour for trains. A 24 hours dwell time was assumed for terminals operating 24/7 (24 hours per days, 7 days per week) and it was increased to 30 hours for terminals that were open 24/5. There was a charge of \$0.7 per mile for rail shipments and a \$3.64 per mile for truck shipments (Fotuhi and Huynh, 2016). There was also a \$150 transfer cost for containers that change mode at intermodal terminals.

The company plans to expand the network for the next 20 years over three expansion periods at years 2020, 2025 and 2030. The expansions affect 15 annual routing periods from 2020 to 2035. 50 to 65 different OD pairs are selected from 44 major cities in U.S.

and their forecasted demand quantities are drawn from Freight Analysis Framework (FAF4) database. The origin and destination of these OD pairs are at least 750 miles apart and their corresponding demand values are more than 125 lb per year. These two conditions are required to make shipments eligible for intermodal shipping option (Fotuhi and Huynh, 2015). FAF4 includes forecasted freight volumes between different zones within U.S for every five years from 2015 to 2045. There is no information available for the forecasted demand of routing periods between expansion periods. Hence, the demand scenarios for these periods are estimated based on the predicted values of demand at expansion periods available at FAF4. Since FAF4 data are in kilo tons, they are converted to their equivalent 40-foot Container units as they are the most standardized units for intermodal shipping.

50 to 200 intermodal trains each carrying 100 to 200 40-foot containers pass major rail corridors of this company per day (C Systematics, 2007). 8500 daily number of trucks move containers on major freight highway corridors (US Department of Transportation). Accordingly, it is assumed that the capacity of roads for freight movement can range from 1000 for rural roads to 8500 for major interstates. Annual demand of each OD pair is divided by 365 to find their average daily demand. Accordingly, the routing subproblems found optimal daily routes for each OD pair based on the average daily demand and capacities of infrastructure. The annual transportation cost is then computed by multiplying the optimal daily routing cost and number of days in a year. Unlike traditional strategic location-routing studies, this method can better capture the traffic congestion (corridor capacities) impact on routing decisions.

The test case considers 5, 4 and 3 disruption and demand scenarios for the first, second and third expansion periods, respectively. The first scenario of each expansion period with the highest chance of occurrence assumes the normal situation in which no disruption happens in the network. Hurricane in New Orleans and Florida, earthquake in state of Washington and Oregon, Ice storm in Midwest and tornado in Midwest are the other 4 scenarios of the first expansion period. There is a small chance of earthquake in California, tornado in Midwest and flooding in lower part of Mississippi river in the second expansion period. Apart from the normal situation, the third expansion period includes two more scenarios as coastal flooding in California and ice storm in Midwest. Each disruption scenario has the maximum severity at the beginning of its corresponding expansion period and the severity is diminished through the routing subperiods. As an example, consider scenario 2 of the first expansion period. The capacity of the terminal in New Orleans is degraded by 80% due to the hurricane at the beginning of the period. For the first routing subperiod of this expansion period (the first year), only 20% of the capacity of terminals is available for routing of freight. Moving to the next routing period which is the second year, the terminal is partially recovered from damages and 50% of its capacity is available for the routing decisions. The same framework exists for the subsequent routing subperiods of this expansion period. It is assumed that disrupted infrastructure is fully recovered by the last routing subperiod of an expansion period. It should be noted that access to real world freight data is not possible so the results are valid for the type of data that this paper considered. Different assumptions in terms of number of expansion and routing periods and problem parameters may change the results.

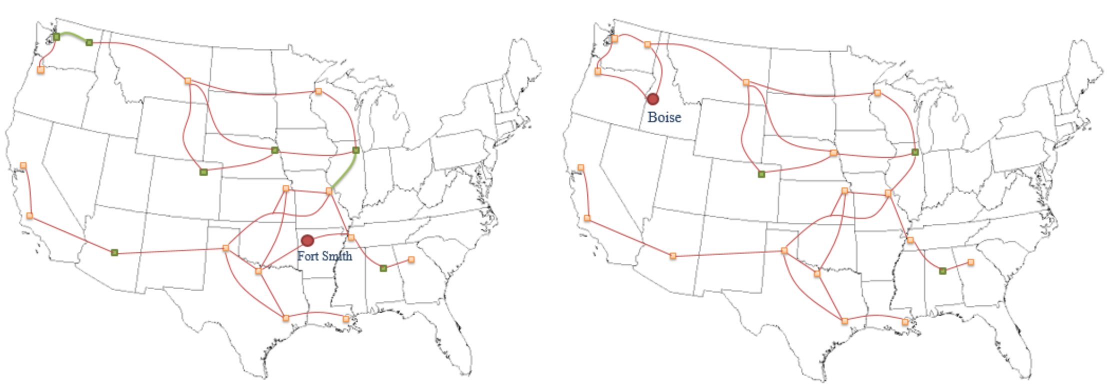
5.6.2.1 IMPACT OF MULTI-PERIOD PLANNING ON NETWORK REPRESENTATION

To investigate the impact of multiple expansion time periods on total transportation cost and terminal's capacity utilization, the multi-period model is compared to the single-period case. Like the small case study, the single-period problem considers maximum number of OD patterns and their corresponding demand quantities as well as maximum disruption percentages for disrupted infrastructure over all scenarios and time periods. The expansion budget is sum of the budget of all expansion periods.

As depicted in Figure 5.6, the optimal decision for single-period problem opens a new terminal in Fort Smith, AR, expands terminals in Seattle, WA; Phoenix, AZ; Birmingham, AL; Kansas City, KS; Denver, CO; Chicago, IL and Spokane, WA. It also retrofits two rail links including Seattle-Spokane and Omaha-Chicago. However, the multi-period framework with three expansion periods has a different optimal design. It opens three new terminals in Boise, ID; Fort Smith, AR; and Jackson, MS in the first, second and third expansion periods, respectively. Birmingham, AL; Denver, CO and Chicago, IL are the three terminals selected for expansion at the first period. No terminal is selected for expansion in the second period and Spokane, WA is the only expanded terminal in the third period. Unlike the single-period design, no budget is spent to retrofit any links in the network. These results show that a remarkable portion of the budget is spent on expanding existing terminals rather than building new ones which is a different finding compared to the multi-priod case. Both designs have mutual new terminals and expanded existing terminals. However, the decisions are made in different time spans for the multi-period case. It is worth mentioning that no link is retrofitted in the multi-period case due to the low chance of disruptions which is relaxed in the single-period case.

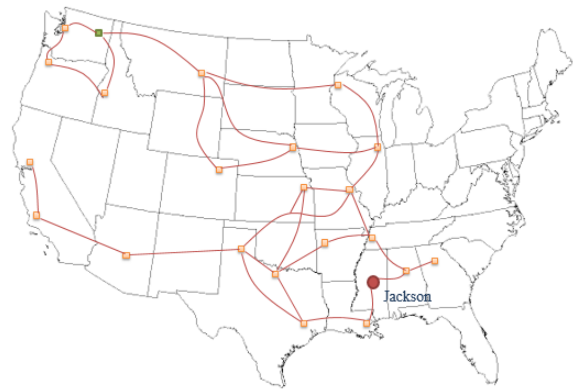
To address the benefit of considering different time scales for expansion and routing, the results of multi-period model with single time scale is compared to the ones for the multi-period model with multiple time scales. The multi-period model with single time scale features the following parameters. It assumes that the demand for each expansion period is the maximum number of ODs and their corresponding quantities over the routing subperiods of that period. The disruption percentages of each expansion period is assumed to be the highest values over the routing subperiods of that period.

The optimal design of the multi-period model with single time scale opens terminals in Fort Smith, AR and Jackson, MS in the second and third time periods, respectively. The whole budget is spent to expand existing terminals in Dallas, TX; New Orleans, LA; Biriminghanm, AL; Denver, CO; Omaha, NB; Chicago, IL and Billings, ID in the first period. Terminal in Seattle, WA is the only one selected for expansion in the second period. The remaining budget in the third period is spent to expand terminals in Billings, MT and Denver, CO. Like the multi-period model with multiple time scales, no link is retrofitted due to the low chance of disruptions at all periods.



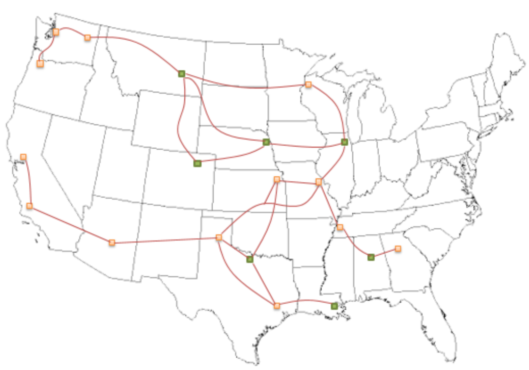
a) Single-period model

b) Multi-period model- multiple time scales (LT=1)



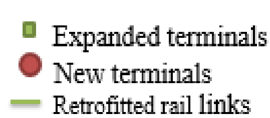
c) Multi-period model- multiple time scales (LT=2)

d) Multi-period model- multiple time scales (LT=3)



e) Multi-period model-single time scale (LT=1)

f) Multi-period model-single time scale (LT=2)



g) Multi-period model-single time scale (LT=3)

Figure 5.6 Optimal network representations of the case study.

5.6.2.2 IMAPCT OF MULTI-PERIOD PLANNING ON CAPACITY UTILIZATION

As depicted in Figure 5.6, a significant portion of the budget is spent to expand 7 terminals and open a new one in the beginning of the planning horizon for the single-period problem. However, this additional capacity is gradually provided over multiple time periods under the multi-period approach. Figure 5.7 depicts the average capacity utilization increase of all open terminals under the multi-period model against the single-period ones for all scenarios under the three expansion periods. In average the daily utilization is increased by 1 to 2 percent. This is reasonable since the multi-period model can better accommodate the continues change in the demand over the planning horizon. Instead of providing extra capacity within a short time (traditional single-period model), the multi-period model adds the extra capacity in the appropriate infrastructure and period. A daily 1% increase can generate a huge revenue for the whole planning horizon. Consider a terminal with a capacity of handling 5000 containers daily. A 1% increase means handling 50 more containers in a day, 18250 more containers in a year and 273750 more containers for the whole planning horizon. If each container can produce 150$ revenue for the intermodal service provider, the total opportunity revenue for the company is about 40 million dollars. Note that the case study is only considering 50 OD pairs within Midwest and Western part of US. Hence, the overall capacity usage of the terminals is low. This will significantly increase by considering all possible OD pairs in the whole US.

5.6.2.3 IMPACT OF MULTI-PERIODPLANNING ON TRANSPORTATION COST AND ROUTING DECISIONS

The single-period model finds a conservative network that can survive worst case scenarios with highest disruptions and maximum number of OD pairs with their highest demand quantities over the planning horizon. This design disregards the low occurrence chance of disruptions and gradual recovery of disrupted infrastructure over time. Accordingly, the total transportation cost under this design is almost 1 billion dollars more for the whole planning horizon which is around 50 million dollars annually compared to the multi-period case with multiple time scales. In a similar situation, the multi-period model with single time scale spends 600 million dollars more in transportation cost for the whole planning horizon which is around 40 million dollars annually. The reason behind such an increase in total cost is ignoring network recovery from disruptions. The gradual capacity recovery of disrupted infrastructure can only be considered in the multi-period model with multiple time scales. When facilities regain their initial capacities through the routing subperiods, more shipments can be transported over their cheapest paths leading to lower overall transportation cost. To clarify this fact, the routing results of one OD pair is discussed in the following.

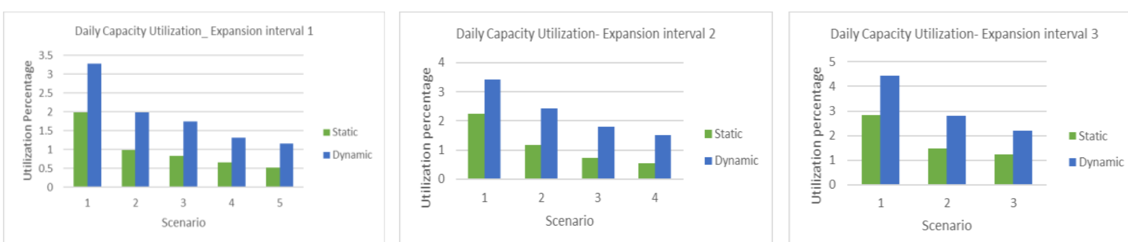


Figure 5.7 Capacity utilization comparison under the multi-period and the Single-period expansion designs

The resulting routing decisions of one OD pair (Los Angeles, CA - Seattle, WA) is depicted in Table 5.2. These routes correspond to five routing subperiods of the first expansion period under the third scenario. As mentioned before, this scenario involves earthquake in states of Washington and Oregon impacting terminals in Seattle and Portland. There is a huge capacity reduction in rail and highway links within these states as well. As shown in Table 5.2, 86% of the demand is routed via an alternative route passing through nearby states with no disruptions in the first routing subperiod with highest disruption severities. Only 14% of the flow is assigned to the shortest path of this OD pair which included links within disrupted states. A remarkable portion of the demand is shifted to the shortest path in the second routing subperiod due to the extensive recovery of disrupted infrastructure. Once the disruption impact is fully resolved in the third routing subperiod, all the flow is assigned to the shortest path for the subsequent routing subperiods of this expansion period. These results verify the benefit of including shorter routing periods in expansion decisions to better consider disruption impacts on routing of freight flow over the network.

Table 5.2 Routing results for a specific OD pair under one expansion period.

Rt	Routes	Percent of flow
1	Los Angeles-Las Vegas- St George- Salt Lake City- Boise- Seattle	86%
	Los Angeles- Oakland- Medford- Portland- Seattle	14%
2	Los Angeles- Oakland- Medford- Portland- Seattle	73%
	Los Angeles-Las Vegas- St George- Salt Lake City- Boise- Spokane- Seattle	27%
3	Los Angeles- Oakland- Medford- Portland- Seattle	100%
4	Los Angeles- Oakland- Medford- Portland- Seattle	100%
5	Los Angeles- Oakland- Medford- Portland- Seattle	100%

5.7 CONCOLUSIONS

This paper developed a mixed integer probabilistic robust model that addresses the intermodal freight network expansion problem using a multi-period planning approach. The model incorporated uncertainties in demand and supply as well as different time scales for expansion and routing decisions. A hybrid simulated annealing algorithm was developed to solve the developed model. The results verified the quality and time efficiency of the algorithm compared to exhaustive enumeration for small-sized and large-sized networks.

The results showed that the multi-period planning approach can significantly reduce the total transportation cost and improve capacity utilization of intermodal terminals compared to the traditional single-period planning approach. They also verified that by considering different time scales for routing and expansion decisions compared to multi-period planning with single time scale a lower transportation cost can be obtained. The results also indicated that the available funds are best used to expand existing terminals or build new ones rather than retrofit weaker links in the network due to the low assumed probability of disruptions.

This work can be extended by incorporating correlated failures in disrupted infrastructure which is more realistic in nature. Furthermore, the model can be generalized to include other transport modes which is necessary if the scope extends to international freight movements. Providing a distribution free model to deal with uncertainties is another important area that can be considered in future work. Incorporating the discounted value of money over time is another important factor that can make the problem more realistic. Instead of assuming the value of currency to stay constant over time, there can be a discounted factor impacting that value.

CHAPTER 6: CONCLUSIONS

In this dissertation, three completed research studies are presented to address real world criteria in intermodal freight network design and expansion. These studies present significant cost reduction and revenue increase for intermodal service providers against traditional models.

The primary objective of an intermodal service provider is to build a network which can operate for a long time with less changes over its operational life. It also must provide the maximum amount of revenue for the provider and satisfy the customer by fully meeting its demand within a predefined delivery due date.

Including competition among intermodal service providers leads to more revenue for a company intending to expand its existing intermodal network. Chapter 3 of this dissertation focuses on proposing a model to find locations of new intermodal terminals for a railroad company which competes with companies offering the same service with overlapping service areas. The model also encounters uncertainty in future demand to find reliable locations which can respond to future changes of the demand immediately. A new SA algorithm is also developed to solve larger sized instances of the model to make the model practical for real life applications. The results from a set of random networks verify efficiency of SA in terms of solution quality and computational time. From a practical perspective, the model finds optimal number of new terminals and their locations that can provide maximum revenue for a railroad company operating in US for the next 30 years.

Chapter 4 presents a new model for intermodal network expansion by addressing uncertainty in both demand and supply. Supply uncertainty stems from natural or human-made disasters that might happen in the network and can make a network element (link or terminal) out of order or significantly reduces its capacity. So, it is important to include these incidents when expanding an intermodal network to mitigate their possible risks. The decisions include locations for new terminals, existing terminals to expand and rail links to retrofit. A hybrid GA algorithm is also proposed to solve this model for large size instances. The numerical results showed algorithm's efficiency in finding optimal solutions in much shorter time compared to commercial optimization solvers. Managerial insights are also drawn from a real world case study. The results show that the company can significantly save cost if they include disruption risks and demand uncertainties in their expansion decisions. It also provides policy recommendations for practitioners of how to spend a limited expansion budget while deciding where to locate new terminals, which existing terminals to expand and which higher risk rail links to retrofit.

Chapter 5 improves the previous model by incorporating the dynamic nature of expansion projects due to limited investment capital. The idea is to gradually expand the network over the planning horizon which is divided into multiple periods. It also features shorter periods for routing versus expansion due to the frequent changes in demand, cost and network capacities which can significantly impact routing costs. The model decides when and where to locate new terminals, expand existing ones and retrofit weak links as well as routing of freight flow over the network. Due to the complexity of this model, a

SA algorithm is proposed to solve it for real size networks. The numerical results on a small case study show the efficiency of the algorithm in terms of computational time and optimality gap. The application of the model on a real size network verifies that the multi-period model leads to lower total transportation cost, higher capacity utilization with lower loss of demand due to disruptions. The results also show the superiority of the multi-period model with different time scales for routing and expansion versus a multi-period model with identical time scales in terms of total transportation cost and capacity utilization.

The case study results recommended different practical actions for the third research paper compared to the second one. Utilizing different robust optimization approaches caused the different policy recommendations. The min-max regret approach assumed identical chance of occurrence for all scenarios (Including normal situation and disruptions) and tried to find a solution for the worst case scenario. However, the third case assumed a more realistic situation in which the chance of disruption occurrence is very low and the final decision is more focused on normal situation with no disruptions.

It is also important to note that the goal of this dissertation was to investigate the impact of incorporating different real world parameters in intermodal network expansion decisions and cost reductions. Since, real world data is not easily accessible, the case study results are not generalizable in terms of the final designs and they depended on the data set that was used. Different data and parameters may lead to different results. However, it is proved that the proposed models can significantly reduce cost, improve routing decisions and accommodate future disruptions and demand fluctuations.

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