AN ABSTRACT OF THE DISSERTATION OF

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Hector A. Vergara

Intermodal freight transportation uses at least two different transportation modes (e.g., truck, rail, ship, air) to move freight loads that are in the same transportation unit (e.g., a shipping container) from origin to destination without handling the goods themselves. The increasing shift to intermodal transportation and the growth of freight transportation demand have resulted in a higher demand for intermodal freight transportation that has been projected to grow even faster in the next few decades. Satisfying this emerging demand will require enhancing the capacity of current intermodal facilities or even the construction of new intermodal facilities. This research addresses the intermodal logistics network design problem which is one of the key strategic planning decisions related to intermodal transportation. To obtain the maximum performance of the intermodal logistics network, two relevant decisions corresponding to the route and mode selection for freight loads were integrated with the facility location problem within the integrated intermodal logistics network design (IILND) problem.

To address the IILND problem, two mathematical formulations were developed. One considered making decisions about arcs of the network while the other considered

making decisions about routes for origin-destination flows in the network. The arc-based formulation modeled the effect of consolidating freight loads at intermodal terminals on the transportation cost by a stepwise function that relates the per container transportation cost to the amount of flow between two nodes. A heuristic approach that combines a genetic algorithm and the shortest path algorithm was developed to efficiently obtain high quality solutions for the arc-based formulation.

Unlike the arc-based formulation, the route-based formulation modeled the effect of consolidating different loads at intermodal terminals on the transportation cost and time using constant discount and delay factors, respectively. Moreover, a composite variable formulation was used for the route-based formulation to incorporate route feasibility constraints within the definition of the composites and avoid explicitly adding them to the model. These modifications reduced the number of variables and constraints significantly when compared to the arc-based formulation. Two solution approaches were developed to find optimal solutions for the route-based formulation, namely a decomposition-based search algorithm and an accelerated Bender's decomposition method. Several sets of computational experiments were completed to evaluate the performance of the proposed mathematical formulations and solutions approaches. Finally, several general insights about the effects of design parameters on solution characteristics were obtained from the computational experiments and directions for future research were identified.

Integrated Intermodal Logistics Network Design

by
Mohammad Ghane-Ezabadi

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Dean of the Graduate School

I understand that my dissertation will become part of the permanent collection of Oregon State University libraries. My signature below authorizes release of my dissertation to any reader upon request.

Mohammad Ghane-Ezabadi, Author

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CONTRIBUTION OF AUTHORS

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INTEGRATED INTERMODAL LOGISTICS NETWORK DESIGN

1 Introduction

1.1 Background

Intermodal freight transportation refers to the use of at least two different modes of transportation to move freight loads in the same transportation unit (e.g., a shipping container) from origin to destination (Macharis & Bontekoning, 2004). Different transportation modes are truck (full truckload), rail, barge, airplane and pipeline. Intermodal freight transportation is an alternative to trucking especially for long haul shipments since it can reduce transportation costs, negative environmental effects, and congestion problems (Limbourg & Jourquin, 2009). Moreover, with marketplace globalization, using more than one transportation mode is sometimes unavoidable for moving international freight loads.

An important strategic planning decision related to intermodal freight transportation is the design of an intermodal logistics network. An intermodal logistics network is formed by the collection of physical locations used for the transfer of freight loads from one transportation mode to another and the connections between these physical locations based on the transportation modes that are available at each one of these locations. A very common network topology that is used in intermodal freight transportation is a hub-based network. In hub-based networks, freight loads first move from their origin to a hub. At the hub, all needed transfers are handled and freight loads are sorted and consolidated to be transported to another hub or to their destination (Alumur & Kara, 2008). In general, an intermodal logistics network consists of n nodes that are the origins and/or destinations of freight loads as well as the locations of existing and potential terminals. Nodes are linked by the existing arcs of single-mode transportation networks connecting pairs of nodes in the intermodal logistics network. Some nodes are physically located at the intersection of at least two single-mode transportation networks allowing the transfer of freight loads between different modes. A node can serve the network as a hub if a terminal is installed at its location. A fixed cost is associated with the installation of a terminal and needs to be considered when designing the network. From the operational perspective, freight loads are picked up from their origins and moved to a hub where they are sorted and consolidated (without splitting the load and maintaining the same transportation unit) before being transferred to their destinations or to another hub if needed. The movement between two nodes can be completed using one of the existing modes of transportation that links those two nodes. As a result, transportation time and cost are different for different links according to the transportation mode that is used (i.e., shipping a load by air takes less time and is more expensive than shipping it by truck). Moreover, even for loads shipped on the same transportation mode, the transportation cost per load depends on the amount of loads that are shipped (i.e., the transportation cost per load decreases as more loads are transported between two nodes, due to economies of scale).

In practice, the design of an intermodal logistics network includes many decisions that are made at different levels of decision making. At the strategic level, hub locations are established by determining the number of hubs that are needed and their locations. At the tactical level, decisions are made with respect to resource levels at hubs such as workforce levels, and number and type of cranes and other material handling and storage equipment that are required based on expected freight traffic flow through the hubs. Finally, at the operational level, decisions are made with respect to the selection of regular routes and transportation modes (i.e. selecting the transportation mode for each of the transportation legs of a route) for shipments associated with the expected demand in the intermodal logistics network. These decisions are not independent; for example changing the number of hubs and their locations can affect the optimal routes for shipments which may affect the total installation and transportation cost. As a result, these decisions should be made together (i.e., in an integrated way) in order to optimize the intermodal logistics network performance. In this context, intermodal logistics network design performance optimization can be defined in one of two ways: minimization of total network cost (i.e., total installation and transportation cost) or maximization of the level of customer satisfaction.

1.2 Problem Definition

The focus of this dissertation research is on the development of mathematical models and efficient solution approaches to solve the Integrated Intermodal Logistics Network Design (IILND) problem. The IILND problem can be defined as the integrated problem of selecting hub locations, assigning routes to freight loads, and selecting the transportation mode for each shipment of a freight load such that the total transportation cost and the fixed cost of installation of hub facilities in the network are minimized subject to operational constraints such as satisfying all customer demands, opening an adequate number of hubs, and selecting feasible routes for each freight load.

1.3 Research Objectives

The objective of this dissertation is to integrate the strategic decision of finding hub locations in an intermodal logistics network with other relevant operational decisions by applying operation research techniques to find high quality solutions in reasonable computational times.

1.4 Research Questions

This dissertation addresses the following questions:

- How to integrate different planning decisions related to intermodal logistics network design in a single mathematical formulation?
- How to incorporate realistic assumptions of intermodal freight transportation operation in a mathematical formulation for integrated intermodal logistics network design?
- How to find high quality solutions for real-size instances of the integrated intermodal logistics network design problem in reasonable computational times?

1.5 Research Tasks

The following research tasks were completed as part of this dissertation:

1. A literature review of relevant research in intermodal transportation, intermodal logistics network design, large-scale optimization, and various solution approaches that have been used to solve similar integrated planning problems in hub location and network design.
2. Development of a basic arc-based mathematical formulation for integrated intermodal logistics network design that models transportation economies of scale due to consolidation utilizing a stepwise function that relates the per load transportation cost to the amount of flow between two nodes.

3. Development of a genetic algorithm-based solution approach that combines a genetic algorithm and the shortest path algorithm to find high quality solutions for the arc-based mathematical formulation of the IILND problem developed in Task 2.
4. Development of a route-based mathematical programming formulation for the IILND problem in which feasible routes between origin and destination for a freight load are modeled as decision variables. This alternative mathematical formulation has fewer constraints and decision variables compared to the arc-based mathematical formulation developed in Task 2.
5. Development of a decomposition-based search algorithm to solve non-trivial instances of the route-based formulation of the IILND problem developed in Task 4 to optimality in reasonable computational times.
6. Development of an accelerated Bender's decomposition approach to solve large instances of the route-based formulation of the IILND problem developed in Task 4 to optimality in reasonable computational times.

1.6 Research Outcomes

The most important research outcomes associated with this dissertation are listed below:

- An arc-based mathematical programming formulation to design intermodal logistics networks that integrates hub location, route and transportation mode selection problems. This formulation considers realistic aspects such as nonlinear transportation costs, availability of more than two transportation modes, and allowing alternative dispatching methods for intermodal freight shipments (i.e., point to point as well as using as many hubs as needed) to reduce transportation costs.
- A heuristic solution approach based on a genetic algorithm to obtain high quality solutions for large instances of the arc-based mathematical model developed in this research in reasonable computational times.
- An alternative route-based mathematical programming formulation to improve tractability for large size instances, and to incorporate other realistic aspects of intermodal transportation such as enforcing service level requirements for the shipments in the network by limiting transportation time between nodes in the network.

- A decomposition-based search algorithm to obtain exact solutions to non-trivial size instances of the route-based mathematical formulation of the IILND problem in reasonable computational times.
- An accelerated Bender's decomposition algorithm to obtain exact solutions to large instances of the route-based mathematical formulation of the IILND problem in reasonable computational times.

1.7 Research Contributions

To address the IILND problem as defined in Section 1.2., two mathematical formulations were developed: an arc-based formulation and a route-based formulation. In the arc-based formulation, a single decision variable is defined for each of the transportation legs in the network. Also, the consolidation effect on transportation cost due to economies of scale is modeled using a stepwise cost function that relates the unit transportation cost per container on each arc to the amount of flow on that arc. While this assumption made the arc-based mathematical formulation more realistic, it increases the complexity of te resulting mathematical model in a way that using metaheuristics was necessary for finding high quality solutions. Therefore, a genetic algorithm-based solution approach was developed to find high quality intermodal network designs.

To overcome the tractability issues observed with the arc-based formulation for realistic size instances of the IILND problem, an alternative route-based formulation was developed in which the economies of scale was modeled using a constant discount factor. The alternative formulation also facilitates incorporating additional realistic elements of the problem to the mathematical model. The route-based formulation was developed by means of composite variables. The defined composite variable denotes a complete feasible route for a load from origin to destination as opposed to having one decision variable for each load movement between a pair of nodes. Moreover, composite variables allow enforcing some of the operational constraints implicitly at the same time feasible routes are being generated instead of adding those constraints to the mathematical model. A decomposition-based search algorithm was developed to obtain exact solutions for small to medium size problems in reasonable computational times.

As the decomposition-based search algorithm has limited applicability since it cannot be applied for solving large size instances of the IILND problem, an alternative way to solve the larger instances of the IILND problem was explored by implementing a Bender's decomposition approach to solve the route-based mathematical formulation. Moreover, a pre-processing heuristic was developed that reduces the size of problem instances and provides a better upper bound for the problem. Using this new solution approach, it is shown that large instances of the IILND problem (with 250 cities and about 12,500 origin-destination pairs) can be solved in reasonable computational times.

The rest of this dissertation is organized as follows. In Chapter 2, the arc-based formulation and genetic algorithm-based solution approach are presented. The alternative route-based formulation and decomposition-based solution approach are presented in Chapter 3. Chapter 4 presents the accelerated Bender's decomposition approach to solve the route-based formulation. Finally, Chapter 5 presents general conclusions about the research completed in this dissertation and future research directions.

2 Integrated Intermodal Network Design with Nonlinear Inter-hub Movement Costs[1]

2.1 Abstract

A critical strategic decision in intermodal transportation planning is the design of its logistics network. In this research, load route and transportation mode selection problems are integrated with the hub location problem in a single mathematical formulation to find the optimal design of intermodal transportation networks. Economies of scale are modeled utilizing a stepwise function that relates the per container transportation cost to the amount of flow between two nodes. A heuristic method combining a genetic algorithm and the shortest path algorithm was developed to efficiently solve this integrated planning problem. Computational experiments were completed to evaluate the performance of the proposed heuristic by comparing the solutions obtained with this method to exact solutions obtained for different problem instances. At the end, conclusions are presented and future research directions are discussed.

Keywords: intermodal; hub network design; integrated planning; integer programming; heuristic; genetic algorithm

2.2 Introduction

Long-haul freight transportation over road, which has been the predominant mode for freight transportation for many decades, produces significant environmental and congestion issues (Crainic and Kim, 2007). Moreover, with marketplace globalization, a large number of international freight movements cannot be handled only by road transportation and multiple transportation modes are needed to connect shippers and customers. In this context, intermodal freight transportation is a valid alternative to road transportation over long distances which can be used to reduce transportation costs, congestion, and negative environmental effects. In general, intermodal freight transportation is defined as using at least two different transportation modes to move freight that is in the same transportation unit (e.g., a shipping container)

[1] This work has been submitted for publication to *Transportation Research Part B: Methodological*

throughout their route from origin to destination without actually handling the goods when changing modes or making transfers (Crainic and Kim, 2007).

One of the key strategic planning decisions in intermodal freight transportation is the design of its logistics network. Different network topologies including point to point, corridor, hub and spoke, connected hubs, static routes and dynamic routes have been used to handle intermodal transportation service (Woxenius, 2007). In this research, a hybrid network topology that combines the connected hubs with the point to point and static routes is implemented for intermodal transportation. Therefore, loads can be shipped directly from their origin to destination or they can be moved from their origins to a hub or terminal. At the hub, all needed transfers are handled and loads are consolidated to be transported to another hub or to their destinations. In this configuration, the larger flows between hubs reduce total transportation costs due to economies of scale resulting from the consolidation of loads. By considering this hybrid network topology, this research is not addressing the traditional hub-and-spoke network design problem anymore.

Since intermodal networks consist of the individual networks of the transportation modes that are integrated, decisions made during the intermodal network design process not only affect the operational performance of intermodal transportation. They also affect the performance of each of the single-mode transportation networks that are involved. Furthermore, several strategic, tactical and operational decisions and constraints need to be considered when designing an intermodal network. For example, hub locations are determined in the strategic phase and affect the selection of resource levels at terminals, and transportation modes to be used which are established at the tactical level. Similarly, the previous decisions affect the selection of specific routes for loads which are determined during the operational phase. These decisions are not independent and should be handled together to optimize the intermodal transportation system performance. However, in most previous research studies, these decisions have been made separately in a multi-stage approach in which decisions made at one level are used as input for the next level. In this research, hub locations, load routing and transportation mode selection for each load are all considered in a single integrated mathematical model to find the optimal design for an intermodal network.

Also in practice, the per container transportation cost depends on the degree of consolidation at terminals due to economies of scale (i.e., transportation cost per container will decrease more as more containers are consolidated at terminals). However, most previous research considers a constant discount factor for all inter-hub transportation movements regardless of the amount of containers (i.e., flow) that is shipped between two nodes (Alumur and Kara, 2008). While we are able to obtain valuable insights by using a constant discount factor, there is a need for a more accurate cost function to make the mathematical formulation more applicable in real world instances. The mathematical model presented in this research considers a stepwise cost function that determines the per container transportation cost as a function of the amount of containers that are shipped between different pairs of nodes. Using this stepwise cost function, we can model real world cost functions accurately. However, considering this stepwise cost function makes the Integrated Intermodal Logistics Network Design (IILND) problem significantly harder to solve. This is because with this stepwise cost function, the route and mode selection problems become NP-hard problems regardless of the hub locations (Chekuri et al., 2006). Note that the hub location problem is also an NP-hard problem even when the economies of scale are modeled using a constant discount factor. In order to solve the IILND problem efficiently, a heuristic method combining a genetic algorithm (GA) and the shortest path algorithm (SPA) was developed.

A particular contribution of this research is that the transportation mode of each shipment leg can be explicitly determined with this new mathematical model in comparison to previous models that only determine the inter-hub shipment transportation mode and assume that all other shipments are handled by truck.

Also, previous research studies restrict the number of hubs that each load can visit in its movement from origin to destination (i.e., usually to two hubs). This assumption may be valid in small logistics networks, however in larger networks especially for long-haul or international transportation, a load may pass through several hubs in order to be consolidated with other loads or be transferred to a different transportation mode to reduce transportation costs. As such, this assumption is relaxed in the current study and loads are allowed to visit as many hubs as needed between origin and destination to reduce the total network cost.

The mathematical model presented in this research relaxes some restrictive assumptions considered in previous models in the literature and can be applied to design more realistic intermodal networks. Moreover, the solution approach developed and implemented in this research can provide high quality solutions in reasonable computational times for small and medium size instances.

The rest of this chapter is organized as follows. In Section 2.3, a review of previous studies in intermodal planning and network design is presented. The formal definition of the problem, mathematical formulation and the solution approach are presented in Section 2.4. The results of the computational experiments completed in this research are presented in Section 2.5. Finally, conclusions and future research directions are presented in Section 2.6.

2.3 Literature Review

As intermodal freight transportation grows within the transportation industry, a growing number of research studies have been completed in this area. Macharis and Bontekoning (2004) categorized these studies according to two criteria: “type of operator” and “time horizon of the operations problem.” Several research studies have been completed in each of these categories. From the type of operator perspective, some relevant examples of drayage operator problems have been recently studied by Caris and Janssens (2009), Jordan Srour and van de Velde (2013), Sterzik and Kopfer (2013), Nossack and Pesch (2013), and Braekers et al. (2014). Challenges faced by terminal operators have been addressed lately by Petering and Murty (2009), Petering (2011), and Chen et al. (2013). Chang (2008), Giannikas and McFarlane (2013), Kengpol et al. (2014), and Tiwari et al., (2014) have studied problems related to third-party logistics (3PL) operators in recent years. Finally, more closely related to the current research, Ishfaq and Sox (2011), Ishfaq and Sox (2012), Sörensen et al., (2012), Sörensen and Vanovermeire (2013), Zhang et al. (2013), Lin et al. (2014) and Ghane-Ezabadi and Vergara (2016) have recently developed models and solution approaches for network operator planning problems.

From the time horizon perspective, research studies have been classified into strategic, tactical and operational planning problems. The design of the intermodal logistics network is one of the most important strategic planning problems that affect the performance of the intermodal transportation system. In this area, hub-and-spoke networks have been studied the most as they are the fundamental network configuration for intermodal freight transportation. Several studies related to the design of hub networks can be found in the literature in many applications related to transportation and telecommunications. Alumur and Kara (2008), Campbell and O'Kelly (2012) and Farahani et al. (2013) provide recent comprehensive reviews of various research studies in this area. However, as a particular application area, intermodal freight transportation has its own characteristics and constraints that should be explicitly considered when designing a logistics network using a hub-based configuration. In particular, most of the hub location literature assumes that no direct shipment between spokes is allowed and that the flow of cargo is limited to visit at most two hubs. These are not realistic assumptions in practice in the context of intermodal freight transportation. Also, most existing work in this area only considers the hub location or hub network design aspect of this problem and ignores the integration of the hub location-allocation decisions with tactical decisions such as mode selection and resource allocation.

In the literature, operations research techniques have been consistently used for designing intermodal logistics networks. However, given the complexity and scale of this planning problem, many researchers have mostly relied on heuristic and metaheuristic approaches to obtain near optimal solutions for large problem instances. Mathematical models for intermodal hub network design applications were initially presented by Arnold et al. (2001), Arnold et al. (2004), and Racunica and Wynter (2005). Smilowitz and Daganzo (2007) proposed an approach for the design and operation of integrated intermodal transportation networks for express package delivery. Rahimi et al. (2008) developed a mixed integer programming model to find the optimal number and location of inland ports for an intermodal transportation network in

California that minimizes total transportation and facility costs. Limbourg and Jourquin (2009) developed an iterative procedure to estimate the potential locations for terminals assuming that each node can be allocated to only one hub in the network. Then, the authors used a mixed integer programming model to determine the optimal locations among those potential locations. Later, Ishfaq and Sox (2011) considered the assumptions that each load has service time requirements and can be shipped through at most two hubs. In this study, the transportation times between two hubs were multiplied by a constant factor to capture the transitioning time at terminals. In a related study, Ishfaq and Sox (2012) modeled the hub operations as a G/G/1 queuing system to estimate the transitioning time at terminals more accurately. In this study, although each terminal can serve different modes of transportation, each load can use only one mode when transported from origin to destination. In both of these last two research studies, a tabu search (TS) metaheuristic was implemented to find near optimal location-allocations of hubs that minimize the total transportation and fixed hub facilities costs.

Sörensen et al. (2012) developed a couple of two-stage metaheuristic methods for the mixed integer programming model first developed by Arnold et al. (2004) which allows direct transportation between nodes as well as visiting at most two hubs. The objective of this model was to determine the location-allocation of hubs such that the total transportation cost is minimized. Lin et al. (2014) improved the mathematical model of Sörensen et al. (2012) by reducing constraints and variables in the formulation without any extra assumptions. The authors then developed two heuristics to find near optimal hub locations. Sörensen and Vanovermeire (2013) modified the model of Sörensen et al. (2012) to a bi-objective mixed integer programming model. The authors developed a problem-specific greedy randomized adaptive search procedure (GRASP) to approximate the optimal Pareto set.

In another study, Alumur et al. (2012) proposed single allocation hub network design models including delivery due date constraints and allowing multiple transportation modes. They used valid inequalities and a heuristic based on Lagrangian decomposition and variable reduction to solve the proposed formulations. Alumur et al. (2012b) also solved a hierarchical hub median problem where shipment of all cargo is restricted to pre-specified time windows by developing a mixed integer programming formulation that is solved with the help of variable fixing rules and valid inequalities. In their model, they minimize the total transportation costs and installation costs per unit of time.

Competition and collaboration considerations have also been incorporated in intermodal hub network design. Meng and Wang (2011) proposed a joint *U*-shaped transportation cost function in their network design formulation when considering different stakeholders and investment budget limitations. In this same area, Vasconcelos et al. (2011) studied the effect on total cost of adding a hub to an existing network operated under decentralized management by looking at the percentage of loads moving through the new hub.

Finally, while most of the previous studies only consider transportation and fixed facility costs, a few recent studies have included other types of costs in the modeling of intermodal logistics networks. For example, Zhang et al. (2013) considered environmental costs in the objective function of their mathematical model by estimating the cost of CO_2 emissions related to each shipment in the intermodal logistics network. The authors used a genetic algorithm to find near-optimal network configurations and multi-commodity flow assignments in the network. CO_2 emissions have also been recently considered in the design of intermodal hub networks by Zhang et al. (2015) and Bouchery and Fransoo (2015).

The reader is referred to comprehensive reviews of research studies in intermodal transportation planning including strategic network design by Macharis and Bontekoning (2004), Caris et al. (2013), and SteadieSeifi et al. (2014). Like most of the previous studies on strategic network design, the current research attempts to minimize the total transportation and fixed facility costs, however the modeling approach of this research integrates the load route and transportation mode selection problems within the hub location problem and relaxes some restrictive assumptions made in previous studies.

2.4 Methodology

2.4.1 Problem Definition

In a hub-based network configuration for intermodal freight transportation there are N nodes representing origins and destinations of loads, and potential locations for hubs. Fixed costs associated with the installation of hubs at these nodes are considered. Containers in a load can be shipped between two nodes using one of the available transportation modes that connect the two nodes. Each transportation mode has a corresponding transportation cost per mile and per container. However, this transportation cost depends on the amount of containers that are transported on a particular mode between two nodes. As flow between hub nodes increases and consolidation occurs with modes that are able to handle more than one container in a single trip, the transportation cost per container decreases due to economies of scale resulting from the larger flows. Consequently, the per container transportation cost of moving freight between two hubs is less than the per container cost of transportation between a hub and a non-hub node or between two non-hub nodes. However, the transportation time between origin and destination also increases as more hubs are involved in a trip due to delays at the hubs for coordination and load handling.

The Integrated Intermodal Logistics Network Design (IILND) problem can be defined as determining the locations for hubs, the assignment of routes to load shipments, and the selection of the transportation mode for each load shipment such that total hub installation and transportation costs are minimized subject to constraints. In particular, our proposed mathematical formulation for the IILND problem presented in Section 2.4.2 attempts to minimize the total hub installation and transportation costs while satisfying constraints for network balance and maximum number of open hubs.

2.4.2 Mathematical Model Formulation

To model the effect of consolidation and economies of scale on the transportation cost for inter-hub movements, a stepwise function that relates the per container transportation cost to the amount of flow between two nodes was utilized in this research, as shown in Figure 2.1. The number of steps in this cost function can be arbitrarily determined based on a particular transportation mode. As a result, the stepwise function can realistically model the transportation cost between two nodes with relatively high precision. This approach is different than other methods that have been previously used in the literature to model transportation costs when consolidation occurs, such as those presented by Croxton et al. (2007, 2003).

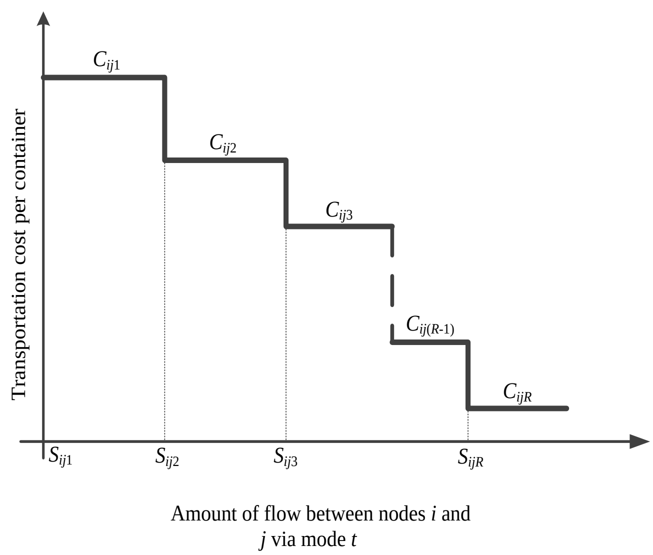

Figure 2.1. Stepwise function for transportation cost per container for mode *t*.

The following notation is used for the proposed mathematical programming formulation of the IILND problem:

<u>Indices and Parameters</u>

$i, j, k = 1, 2, \dots, N$	indices for denoting nodes,
F_i	fixed cost of installing a hub at node *i*,
$t = 1, 2, \dots, T$	index for denoting modes of transportation,
$p, q = 1, 2, \dots, L$	indices for denoting load shipments,
$r = 1, 2, \dots, R$	index for denoting steps in the transportation cost per container stepwise function,
d_p	demand (i.e., number of containers) for load shipment *p*,
S_{ijr}^t	lower bound flow value of step *r* in the transportation cost per container stepwise function between nodes *i* and *j* via mode *t*,

C_{ijr}^{t}	value of step *r* in the transportation cost per container stepwise function between nodes *i* and *j* via mode *t*,
H	maximum number of hubs to be opened,
M	a very large integer number,
$Origin_p$	origin node for load shipment *p*.

Decision Variables

$$Y_i = \begin{cases} 1 & \text{if hub } i \text{ is open,} \\ 0 & \text{otherwise,} \end{cases}$$

$$X_{ij}^{p,t} = \begin{cases} 1 & \text{if load shipment } p \text{ is moved from node } i \text{ to node } j \text{ via mode } t, \\ 0 & \text{otherwise,} \end{cases}$$

$$Z_{ijr}^{p,t} = \begin{cases} 1 & \text{if number of containers for load shipment } p \text{ moving from node } i \text{ to node } j \text{ via mode } t \text{ is on the } r^{th} \text{ step of the transportation cost per container stepwise function,} \\ 0 & \text{otherwise.} \end{cases}$$

Mathematical Formulation

The mathematical formulation for the IILND problem using binary decision variables follows:

$$\text{Minimize } \sum_{i} F_i Y_i + \sum_{p}\sum_{t}\sum_{i}\sum_{j}\sum_{r} C_{ijr}^{t} d_p Z_{ijr}^{p,t} \tag{2.1}$$

Subject to:

$$\sum_{t}\sum_{k} X_{ki}^{p,t} - \sum_{t}\sum_{j} X_{ij}^{p,t} = \begin{cases} -1 & \text{if } i \text{ is origin of } p \\ 1 & \text{if } i \text{ is destination of } p \\ 0 & \text{otherwise} \end{cases} \qquad \forall p \in L, \forall i \in N \tag{2.2}$$

$$\sum_{t}\sum_{j} X_{ij}^{p,t} d_p \leq MY_i \qquad \forall p \in L, \forall i \in N - \{Origin_p\} \tag{2.3}$$

$$\sum_{i} Y_i \leq H \tag{2.4}$$

$$S_{ijr}^{t} - \sum_{q} X_{ij}^{q,t} d_q < M\left(1 - Z_{ijr}^{p,t}\right) \qquad \forall i,j \in N, \forall r \in R, \forall t \in T, \forall p \in L \qquad (2.5)$$

$$\sum_{q} X_{ij}^{q,t} d_q - S_{ijr}^{t} \leq M\left(1 - Z_{ij(r-1)}^{p,t}\right) \qquad \forall i,j \in N, \forall t \in T, \forall p \in L, r = 2, \dots, R \qquad (2.6)$$

$$\sum_{r} Z_{ijr}^{p,t} = X_{ij}^{p,t} \qquad \forall i,j \in N, \forall t \in T, \forall p \in L \qquad (2.7)$$

$$Y_i = \{0,1\} \qquad \forall i \in N \qquad (2.8)$$

$$X_{ij}^{p,t} = \{0,1\} \qquad \forall i,j \in N, \forall t \in T, \forall p \in L \qquad (2.9)$$

$$Z_{ijr}^{p,t} = \{0,1\} \qquad \forall i,j \in N, \forall r \in R, \forall t \in T, \forall p \in L \qquad (2.10)$$

Objective function (2.1) minimizes the total cost consisting of the fixed hub installation cost and the transportation cost for all flows in the network. Constraint (2.2) enforces flow balance at the nodes in the network. Constraint (2.3) requires that hubs should be used only if they are selected to be opened. The total number of hubs that can be opened is limited by constraint (2.4). The transportation cost per container stepwise function is linearized using constraints (2.5) – (2.7). And finally, constraints (2.8) – (2.10) are the variable type constraints. Note that the value of M could be replaced by the summation of all flows in the network ($\sum_p d_p$) to provide a specific bound for constraints (2.3), (2.5) and (2.6).

2.4.3 Solution Approach

As different decisions (i.e., hub location, route and mode selection) are integrated into a single mathematical model, the tractability of the IILND problem presented in Section 2.4.2 is affected by the size of the instances solved. As a result, only small problem instances can be solved to optimality in reasonable times with this formulation using a commercial solver. To overcome this challenge, a heuristic approach that takes advantage of both Genetic Algorithms (GA) and the Shortest Path Algorithm (SPA) was developed in this research. The proposed heuristic method is the iterative procedure illustrated in Figure 2.2, where K is the number of iterations performed by the solution approach. The method starts by finding the optimal location for a single hub in the logistics network and evaluating the resulting total network cost during the first iteration. The method then moves to the next iteration by increasing the number of hubs to open until opening one more hub increases the total network cost of the solution obtained. During each iteration, the SPA is used to find optimal load routes and transportation modes for all freight loads for a given hub location solution. The resulting total network cost is used to evaluate the fitness of that particular hub location solution. Meanwhile, the GA leads the search for optimal hub locations through the feasible solution space. Therefore, the proposed solution approach starts each iteration with a set of initial hub location solutions, then evaluates them using the SPA, and moves to a new set of hub location solutions by applying GA operations until reaching a stopping criterion.

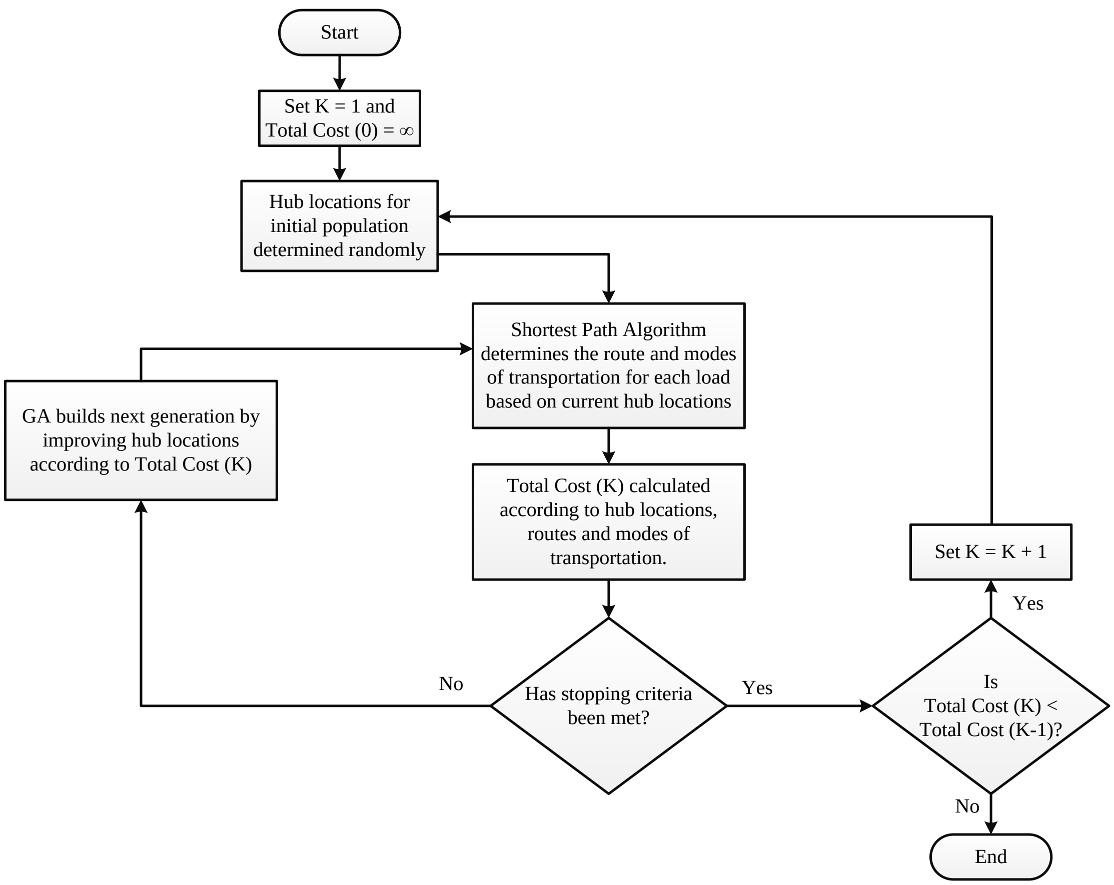

Figure 2.2. Flowchart of the heuristic solution approach.

In the proposed GA, chromosomes represent the allocation of hubs to nodes in the network (i.e., each gene corresponds to the index of a node where a hub is located). Since in the K^{th} iteration of the algorithm, the number of open hubs is equal to K, each chromosome in the population has K genes. For example, if N is equal to 20 and K is equal to 3, a chromosome associated with the solution in which hubs are allocated to nodes 4, 12 and 16 is represented by (*4,12,16*). The initial population for the GA is randomly generated at the beginning of each iteration of the solution approach (i.e., when the number of hubs is increased by one).

To evaluate the hub solutions in each generation of the GA, the total cost for each solution has to be computed. Note that hub locations are fixed for each solution, so the fixed cost of installation is known. However, the transportation cost is not known until the load routes and transportation modes are determined for all loads. The SPA is used to select the route and transportation modes that minimize the transportation cost for a given load. The SPA can only be applied to networks that have at most one link (i.e., arc) with a fixed cost between two nodes. However, in intermodal transportation networks, there can be multiple arcs between two nodes each representing a different mode of transportation. Also, the transportation costs vary as a function of the amount of containers (i.e., flow) that are shipped on an arc. To overcome these challenges, dummy nodes are defined at locations where multiple transportation modes are available. Each single-mode transportation network is modeled by a set of n dummy nodes and the cost of transitioning loads from a node to its corresponding dummy nodes (i.e., nodes in the same location for different transportation modes) is zero. Figure 2.3(a) shows a network with three nodes and two transportation modes. The equivalent network with dummy nodes which is solvable by the SPA is shown in Figure 2.3(b). The corresponding transportation costs per container are shown on the arcs.

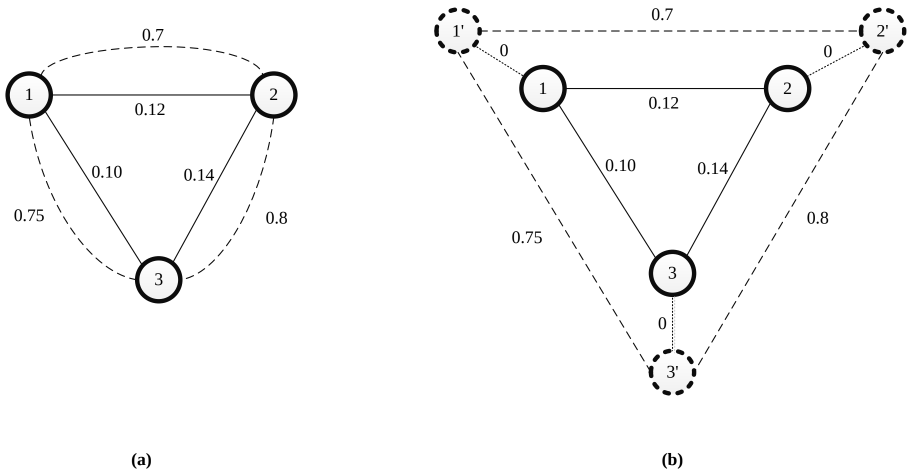

Figure 2.3. (a) A network with three nodes and two transportation modes; **(b)** Same network with dummy nodes.

At this stage of the proposed solution approach, an iterative procedure is implemented to overcome the non-linear transportation cost between nodes in the network. After the SPA is initially used to determine the load routes and transportation modes for all shipments, the transportation costs per container are recalculated based on the amount of flow between each pair of nodes according to the stepwise transportation cost per container function. Then, the SPA is applied again to the network with the new transportation costs. This iterative process continues until no changes in cost are observed. Note that a constant discount factor could be considered for inter-hub shipments in the initial step to generate solutions that incorporate the consolidation of flow. After all load route and transportation mode selection decisions are finalized, the total cost is calculated and used as the fitness value of each hub solution in the current GA population.

A combination of elitism and rank selection is utilized to determine the solutions that are used as input for crossover and mutation operations of the GA. The offspring that result from the application of these GA operations form the population for the next generation of the GA.
The entire process combining the GA with the SPA is repeated until a predetermined number of generations (i.e., the stopping criterion) are produced. Specific details about the implementation of the GA are presented in Appendix A. The pseudo-code that is used in each iteration of the developed heuristic solution method is presented in Figure 2.4.

```
Generate the initial population randomly
While (predetermined numbers of generations are produced) {
    For each solution in current generation {
        Set C_ij^t ← C_ij1^t for all pairs of non-hub nodes
        Set C_ij^t ← discount factor × C_ij1^t for all pairs of hub nodes
        While (no transportation unit cost changes) {
            Run the shortest path algorithm to select the mode and route for each shipment
            Recalculate the costs according to the amount of flows between each pair of nodes
        }
        Calculate the total cost for each solution in the population as their fitness value
    }
    Choose the elite solutions and move them to the next generation
    Do until the next generation has a complete population {
        Select the two parents according to the rank selection
        Do the crossover and mutation operations to generate two children
        Add these two children to the next generation
    }
}
Return the hub locations, route and modes of transportation for each shipment.
```

Figure 2.4. Pseudo-code of the heuristic solution algorithm.

After the GA stops at the end of each iteration, the total cost of the best solution in that iteration is compared to the total cost of the best solution in the previous iteration. If the total cost decreases compared to the previous iteration; the solution method moves to the next iteration by adding one more hub to the number of open hubs and continues to explore an additional reduction in total cost. Otherwise, the solution method stops.

2.5 Computational Experiments

Both, randomly generated instances and the Civil Aeronautics Board (CAB) dataset were used to evaluate the performance of the proposed mathematical model and solution approach. The following sub-sections present the experimental design and computational results for both datasets.

2.5.1 Randomly Generated Dataset

2.5.1.1 Experimental Design for Randomly Generated Dataset

Two sets of computational experiments (Set A and Set B) were completed on randomly generated datasets. Set A experiments were used to test the performance of the proposed heuristic when compared to exact solutions obtained for small network instances. Set B experiments were developed to obtain insights about the solutions obtained with the heuristic method for medium size instances. For all computational experiments, random instances of complete networks (i.e., networks where all pairs of nodes are connected to each other by an arc) were generated in which nodes were uniformly distributed in a 1.0 × 0.5 rectangular area. For each problem configuration in Set A, 10 random instances were generated, while five random instances were created for Set B. In all cases, L loads were randomly generated and their demand (i.e., number of containers) was assigned based on a random value uniformly distributed between 50 and 150 units. In Set A, the size of L was set to be equivalent to 5%, 10%, 15%, 20% and 25% of all possible O-D pairs in the complete network. In Set B, the size of L was set to be equivalent to 20% of all possible O-D pairs. In addition, limitations were established for the number of transportation modes considered in each problem instance. Half of the generated problem instances had only two transportation modes, while the other half considered three modes.

Regarding cost parameters, the fixed cost of installing a hub at a node (amortized for the length of the planning horizon) was considered to be a random variable that is uniformly distributed between 100 and 150. Also, the transportation cost between nodes i and j was dependent on the transportation mode selected to connect two nodes. Values for the first step of the transportation cost per container stepwise function were calculated using equations (2.11), (2.12) and (2.13), according to the number of available transportation modes connecting nodes i and j. Based on our notation, a higher numbered transportation mode was assumed to provide a less expensive transportation cost per container for long haul shipments, while it was more expensive for short haul transportation. In equations (2.11) - (2.13), *Random*(0,1) refers to a uniformly distributed random variable between 0 and 1. Three steps were considered for the transportation cost per container stepwise function for each transportation mode as shown in Figure 2.5.

Mode (t)	Maximum transportation cost per container between nodes i and j (C^t_{ij1})	
1	$C^1_{ij1} = Distance\ (i,j)\ /\ 2 + Random(0,1)$	(2.11)
2	$C^2_{ij1} = Distance\ (i,j)\ /\ 3 + Random(0,1) + 0.05$	(2.12)
3	$C^3_{ij1} = Distance\ (i,j)\ /\ 4 + Random(0,1) + 0.10$	(2.13)

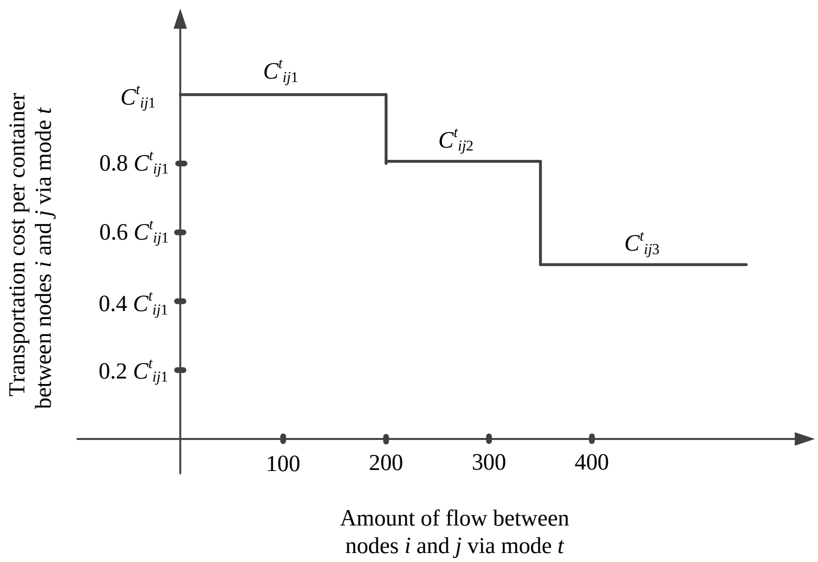

Figure 2.5. Transportation cost per container stepwise function for all transportation modes.

All of the parameters and their respective values used to randomly generate problem instances for both sets A and B are shown in Table 2.1.

Table 2.1. Parameters and values used in computational experiments with Sets A and B.

Parameter	Set A	Set B
Number of Nodes	10	25, 50
Number of loads	5%, 10%, 15%, 20% and 25% of all possible O-D pairs	20% of all possible O-D pairs
Number of Modes	2, 3	2, 3

For the GA used in the proposed solution method, the stopping criterion was set at 50 generations, each containing 40 chromosomes (i.e., hub solutions).

2.5.1.2 Computational Results for Randomly Generated Dataset

The proposed mathematical model and solution approach for the IILND problem were implemented in MATLAB. All computational experiments were run on a 2.83 GHz Quad Core computer with 8 GB of RAM.

2.5.1.2.1 Set A Computational Results

Each instance in Set A was solved using the heuristic solution approach presented in Section 2.4.3, and the results were compared to optimal solutions obtained using CPLEX 12.2 to assess the performance of the proposed solution approach. The percentage differences between the average optimal solution value obtained with CPLEX and the average heuristic solution value for each problem instance were calculated and are presented in Table 2.2. At the same time, a comparison of the selected hub nodes in both solutions was completed and the average percentage of hubs in the heuristic solution that are present in the optimal solution for each problem instance are also shown in Table 2.2.

Table 2.2. Average percentage cost difference from optimal solution and average percentage of optimal hubs in heuristic solution for Set A 10 node networks.

# of Loads	# of Modes = 2		# of Modes = 3	
	Avg. % Cost Diff.	Avg. % Opt. Hubs	Avg. % Cost Diff.	Avg. % Opt. Hubs
5	0.00	100	0.00	100
9	0.50	100	0.54	100
14	1.00	85	0.60	80
18	3.62	75	1.57	80
23	3.47	70	2.88	50

As shown in Table 2.2, the heuristic approach consistently obtained solutions that were very close to the optimal solution. Actually, the heuristic approach obtained the optimal solution for all instances with five loads. However, the average percentage cost difference increased with the size of the problem (i.e., as the number of loads increased), but never exceeded 4% with respect to the optimal solution obtained with CPLEX. Note that increasing the number of modes in the network won't increase the total network cost, but it can decrease it since it increases the alternatives for route and mode selection. It is observed in Table 2.3, that exploring these extra alternatives requires more time, so the solution time increases with the number of transportation modes in the network. However, increasing the number of modes in the network doesn't reduce the quality of heuristic solutions. Therefore, no trend is observed in Table 2.2 regarding the relationship between the number of modes in the network and the average percentage cost difference.

Also, according to Table 2.2, a relationship between instance size and average percentage of optimal hubs found by the heuristic method was observed. For example, in average 70% of the hubs selected in the optimal solution were found by the heuristic method in instances with 23 loads and two modes. This means that even when the average percentage cost difference was about 3.5%, most of the hubs selected by the heuristic were part of the optimal set. Note that the selection of hubs by the heuristic method was the same as the optimal hub selection obtained with CPLEX in small instances with fewer loads. However, as instance size increased, the percentage of optimal hubs found by the heuristic approach decreased.

In terms of computational performance, the average solution times for the heuristic and the exact approaches are reported in Table 2.3. In the instances with fewer loads, the average solution time using CPLEX (i.e. the exact approach) is competitive when compared to the heuristic approach. However, as the size of the instances increased, the average solution time for the exact approach increased very fast while the increase in solution time for the heuristic method was not as significant. In larger instances with 23 loads and three modes, the heuristic approach was able to find a high quality solution in less than two minutes, while it took about 2.3 hours to find the optimal solution using CPLEX. Note that in the exact approach, in addition to the solution time, there is a setup time in which the model is setup to be solved by CPLEX. The setup time depends on the number of constraints and decision variables in the mathematical formulation presented in Section 2.4.2. For networks with 10 nodes, five loads and two transportation modes there were 6,096 constraints, and the average setup time was 14 seconds. While networks with 10 nodes, 23 loads and three transportation modes had 41,838 constraints and an average setup time of 1,476 seconds.

Table 2.3. Average solution times for heuristic and exact approaches for Set A 10 node networks.

# of Loads	# of Modes = 2		# of Modes = 3	
	Heuristic (secs.)	**Exact (secs.)**	**Heuristic (secs.)**	**Exact (secs.)**
5	10	1	17	2
9	19	7	30	9
14	30	49	44	156
18	41	620	64	1,010
23	67	5,024	87	8,500

2.5.1.2.2 Set B Computational Results

While the instances in Set B were not solved to optimality using CPLEX, solutions were obtained by applying the proposed heuristic method. Table 2.4 shows the total network costs and the number of open hubs for all instances in Set B.

Table 2.4: Total cost and the number of open hubs for five Set B instances of complete networks with 25 and 50 nodes.

Instance	Measure	$N = 25, P = 120$		$N = 50, P = 490$	
		$T = 2$	$T = 3$	$T = 2$	$T = 3$
1	**Cost**	4,503.9	3,991.6	13,277.9	12,973.0
	# of Hubs	4	4	5	5

2	**Cost**	4,792.4	4,390.4	13,987.8	13,023.4
	# of Hubs	5	4	5	4
3	**Cost**	4,900.1	4,394.4	14,230.4	13,430.0
	# of Hubs	5	3	5	5
4	**Cost**	4,797.9	4,136.2	14,180.6	12,696.2
	# of Hubs	5	4	5	5
5	**Cost**	4,862.4	4,367.8	14,183.2	12,755.6
	# of Hubs	5	3	5	5

According to Table 2.4, as the number of transportation modes increases from $T = 2$ to $T = 3$ the total network cost reduces. A reason for this is that the networks with three modes consist of the exact same modes as the networks with two modes plus an additional set of dummy nodes associated with transportation mode 3 which provides less expensive long-haul transportation. In this way, the solution space of the route selection problem grows as the number of modes increases. This results in finding better solutions with lower transportation costs. On the other hand, the number of open hubs decreases when a third transportation mode is considered since a new hub is opened only if the amount of savings that result from the additional consolidation of loads is greater than the fixed cost of opening an additional hub. However, when a third transportation mode that provides less expensive long-haul service is considered, the total transportation cost decreases and there is a reduced chance that opening a new hub is economically feasible. Also, as the network size increased from 25 to 50 nodes, a greater than or equal number of hubs were required, although the increase was not really significant.

Regarding the computational performance of the proposed heuristic method for these larger problem instances, Figure 2.6 shows the average solution times obtained for Set A (i.e., 10 node networks) and Set B (i.e., 25 and 50 node networks) instances with load demand for 20% of all possible O-D pairs. According to Figure 2.6, average solution times increased with the size of the instances (i.e., number of nodes and number of transportation modes). The proposed heuristic method was able to obtain solutions in a few minutes for 10 node networks with up to three transportation modes. However, it required more than 53 hours for networks with 50 nodes and three transportation modes. The average solution times for networks with three transportation modes were larger than the solution times for networks with two modes, especially for 50 node networks. Given that the number of dummy nodes and arcs in the network increases with the number of modes in the network, it takes longer for the SPA to find the optimal routes for loads in these instances.

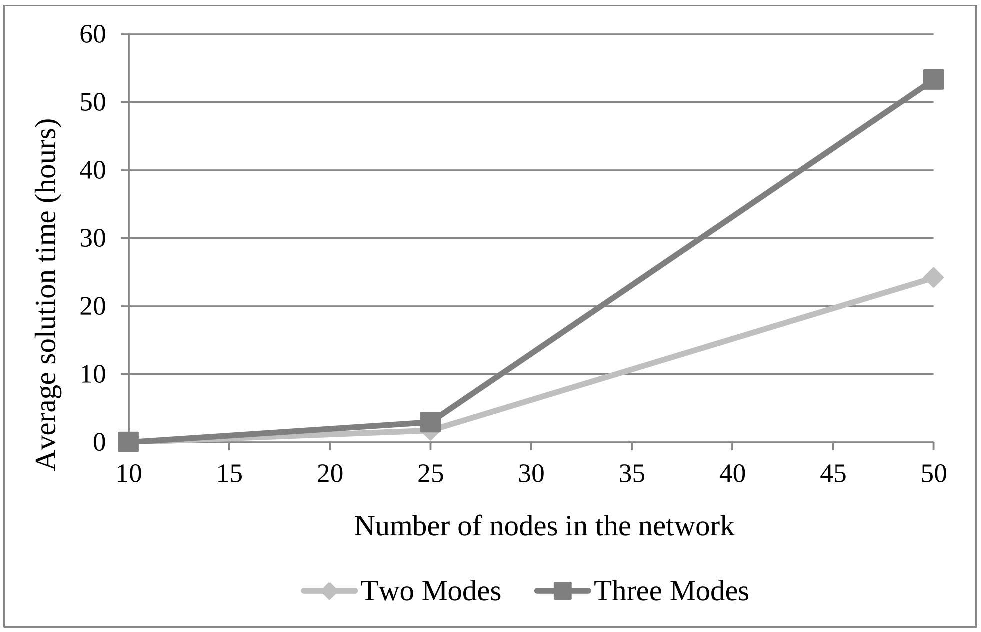

Figure 2.6. Average solution time for the heuristic method for different number of nodes in complete networks with load demand for 20% of all possible O-D pairs.

2.5.2 Civil Aeronautics Board (CAB) Dataset

2.5.2.1 Experimental Design for the CAB Dataset

The Civil Aeronautics Board (CAB) dataset is one of the most commonly used datasets for testing hub location formulations and solution methods. Even though the CAB dataset is not designed for intermodal transportation networks, it was modified for evaluating the performance of the developed mathematical formulation and solution approach in a realistic instance. The CAB dataset consists of the 25 largest cities in the United States in which all possible origin-destination pairs have a positive demand. In our experimentation, the container transportation cost between nodes *i* and *j* was determined based on the transportation mode selected to connect two nodes and the distance between these nodes. Values for the first step of the transportation cost per container stepwise function were calculated using equations (2.14), (2.15) and (2.16), according to the number of available transportation modes connecting nodes *i* and *j*. The CAB dataset was solved considering both two and three transportation modes to evaluate the effect of integrating more transportation modes on the performance of the resulting intermodal logistics networks.

Mode (*t*)	**Maximum transportation cost per container between nodes *i* and *j* (C^t_{ij1})**	
1	$C^1_{ij1} = Distance\ (i,j)\ /\ 25{,}000$	(2.14)
2	$C^2_{ij1} = Distance\ (i,j)\ /\ 40{,}000$	(2.15)
3	$C^3_{ij1} = Distance\ (i,j)\ /\ 50{,}000$	(2.16)

Similar to the randomly generated dataset, three steps were considered for the transportation cost per container stepwise function for each transportation mode as shown in Figure 2.5. In addition, regarding the fixed cost of installing a hub at a node, two different scenarios where considered. In the first scenario, all nodes had the same fixed hub installation cost. The CAB dataset was solved considering fixed costs are 5,000, 10,000, 25,000 and 50,000. In the second scenario, the fixed hub installation cost was not equal for all nodes and was proportional to the total amount of demand flow of each node. In this scenario, the fixed hub installation cost was calculated using equation (2.17).

$$F_i = \frac{Total\ demand\ flow\ of\ node\ i}{\theta} \tag{2.17}$$

Where θ represents a proportionality constant. The CAB dataset was solved considering four different values of θ. All of the parameters and their respective values used to generate problem instances using the CAB dataset are shown in Table 2.5.

Table 2.5: Parameters and values used in computational experiments of CAB dataset.

Parameter	Scenario I	Scenario II
Number of Nodes	25	25
Number of loads	100% of all possible O-D pairs	100% of all possible O-D pairs
Number of Modes	2, 3	2, 3
Fixed Cost	5,000, 10,000, 25,000 and 50,000	-
θ	-	10, 20, 50 and 100

2.5.2.2 Computational Results for the CAB Dataset

Solutions for the CAB dataset were obtained by applying the proposed heuristic method. Table 2.6 shows the total network costs and the number of open hubs for different values of fixed hub installation cost and different number of transportation modes in the network.

Table 2.6: Total cost and number of open hubs for CAB dataset when hub installation costs are equal for all nodes (Scenario I)

			***T* = 2**			***T* = 3**		
N	***P***	F_i	**Total Cost**	**% Fixed Cost**	**# of Hubs**	**Total Cost**	**% Fixed Cost**	**# of Hubs**
25	600	5,000	135,344	7.39	2	110,275	9.07	2
25	600	10,000	145,344	13.76	2	120,275	16.63	2
25	600	25,000	162,949	15.34	1	135,359	18.47	1
25	600	50,000	187,949	26.60	1	160,359	31.18	1

When the hub installation cost is large, the amount of savings that results from opening a new hub does not compensate the fixed cost of opening an additional hub. Therefore, according to Table 2.6, the number of open hubs depends on the fixed hub installation cost at each node.

Moreover, increasing the fixed installation cost from 5,000 to 50,000 increases the percentage of fixed cost in the total network cost from about 7% to 26% when there are two transportation modes in the network.

Even though integrating more transportation modes can increase planning costs as more stakeholders are involved that may have conflicting interests, it was shown to reduce the transportation cost. Planning costs of integrating more transportation modes into a single intermodal transportation logistics network are not considered in this research and are a potential area for future research.

Similar to Scenario I, in Scenario II, the number of open hubs increases by decreasing the fixed hub installation cost, while the transportation cost decreases by increasing the number of transportation modes integrated in the intermodal network (Table 2.7).

Table 2.7: Total cost and number of open hubs for CAB dataset when fixed hub installation costs are proportional to the total amount of demand flow of each node (Scenario II).

				***T* = 2**			***T* = 3**		
N	***P***	***θ***	***Fixed Cost***	**Total Cost**	**% Fixed Cost**	**# of Hubs**	**Total Cost**	**% Fixed Cost**	**# of Hubs**
25	600	10	(19,665-289,546)	179,239	25.77	2	152,631	30.27	2
25	600	20	(9,832-144,773)	126,591	31.67	3	102,074	39.28	3
25	600	50	(3,933-57,909)	118,301	61.31	5	94,329	68.33	5
25	600	100	(1,966-28,954)	117,512	27.42	5	93,903	38.12	5

2.6 Conclusions and Future Work

Designing the intermodal logistics network is one of the critical strategic decisions in intermodal transportation planning. While integrating tactical and operational decisions such as transportation mode and load route selection, and explicitly considering more realistic assumptions when modeling this problem increase the potential applicability of the resulting logistics network design, the complexity of the integrated mathematical model is significantly affected. Consequently, obtaining high quality solutions in reasonable times is very valuable in this context. In this research, a heuristic approach combining a genetic algorithm and the shortest path algorithm was developed to solve this integrated planning problem.

According to the experimental results, solutions obtained with the proposed heuristic approach are very close to the optimal solution for small problem instances with 10 nodes. However, the percentage cost difference between optimal and heuristic solutions increases with the size of the problem. More importantly, the average percentage of optimal hubs found by the heuristic solution approach is large even as instance sizes grow. In fact, the heuristic solution approach was able to obtain all optimal hubs for several small instances. In these cases, the difference between the total cost obtained using the heuristic method and the optimal solution was due to the selection of non-optimal routes and transportation modes by the heuristic method. Consequently, improving the load route and transportation mode selection portion of the heuristic approach is a potential area for future research.

Also, additional criteria such as transportation time can be incorporated into the mathematical model formulation. For example, in real world problems, each load has a time window constraint that is imposed to satisfy service level requirements. Each shipment would take a different amount of time to move between a given node pair depending on the mode of transportation that is selected. Load consolidation at terminals also takes some time depending on the resource levels at terminals and coordination capabilities of the network operators. Including congestion at terminals would be an interesting extension to the proposed formulation. Finally, by considering transportation time in the mathematical formulation of this problem, some other related operational and tactical decisions that influence the intermodal logistics network design problem could be integrated. For example, the determination of resource levels at terminals. The integration of these decisions would improve the practical applicability of the designed logistic networks and is another area for future research.

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2.8 Appendix A

Genetic Algorithm Parameters and Operations

The parameters used in the implemented GA presented in Section 3 were selected based on suggested values for appropriate GA convergence as described by Mitchell (1998). The parameter values were fine-tuned through preliminary testing. The selected parameter values are:

$P_e = 0.1$ Elitism parameter

$P_c = 0.6$ Probability of crossover

$P_m = 0.2$ Probability of mutation

Selection: A combination of elitism and rank selection was utilized in the selection phase of the GA. In each generation, the chromosomes were sorted according to their fitness value and the top P_e percent were chosen to be moved directly to the next generation. The elitism procedure protects the best chromosomes against possible destruction by crossover or mutation operators (Mitchell, 1998). To form the remaining chromosomes for the next generation, an appropriate number of parents was selected among the current chromosomes to be the input for the crossover and mutation operators. The expected value for each chromosome to be selected as a parent was determined according to its rank using the following equation (2.18) given by Mitchell (1998).

$$\text{Expected value of chromosome } i = 0.9 + 0.2\,\frac{(\text{Population} - \text{Rank}_i)}{(\text{Population} - 1)} \qquad (2.18)$$

In order to produce two children, two parents were selected from the current generation according to their expected value and the crossover and mutation operations were applied to them. The purpose of using rank selection was to prevent a very quick convergence of the GA Mitchell (1998).

Crossover: After two parents were selected, the crossover operation was applied to them with probability P_c. A random single crossover point was selected on both parents' strings and all of the genes after that single point were swapped between the two parents. The genes of each child were checked and if any repeated gene was detected, the repeated gene was swapped with another gene of the other child so that the length of chromosome did not change.

Mutation: In order to maintain the genetic diversity from the current generation to the next one, the mutation operation was applied to the children produced in crossover. The mutation operation changed the value of a gene with probability P_m. The new value of the mutated gene was checked with existing genes in the chromosome and if any repeated gene was detected, the repeated gene was mutated again so that the length of chromosome did not change.

3 Decomposition Approach for Integrated Intermodal Logistics Network Design[2]

3.1 Abstract

The integrated intermodal logistics network design problem consists of determining terminal locations and selecting regular routes and transportation modes for loads. This problem was formulated using a path-based formulation and a decomposition-based search algorithm has been proposed for its solution. Computational results show that this approach is able to obtain optimal solutions for non-trivial problem instances of up to 150 nodes in reasonable computational times. Previous studies have only been able to obtain approximate solutions for network problems of this size. A few general insights about the effects of design parameters on solution characteristics were also obtained.

Keywords: intermodal transportation; logistics; hub network; network design; decomposition

3.2 Introduction

In the current environment of marketplace globalization, there is a greater chance that suppliers would need to reach customers that are physically very distant apart. In this context, suppliers would require using long-haul transportation services more often to send their products to those distant customers. Most of the long-haul transportation demand in the United States and other parts of the world is handled using road transportation (i.e., trucking). However, despite the economical aspect of using this transportation mode and the resulting service level provided to customers, road transportation also produces significant environmental and road congestion problems (Crainic and Kim, 2007). To overcome these challenges, policy makers have started to promote the use of intermodal freight transportation as an alternative to road transportation. For example, the European Commission has started the Marco Polo program in Europe to incentivize the shift of a significant portion of freight demand from road to other transportation modes (European Commission, 2014).

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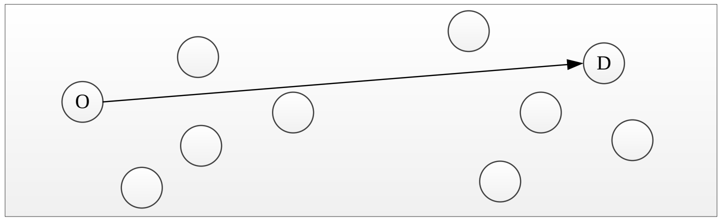
Intermodal freight transportation consists on the use of at least two different transportation modes to move freight loads that are in the same transportation unit (e.g., a shipping container) from origin to destination without handling the goods themselves (Macharis and Bontekoning, 2004). In recent years, the demand for intermodal freight transportation has continuously increased and this trend is expected to remain the same in the future. In this context, the installation of additional intermodal infrastructure will be necessary to fulfill potential future demand. The way in which the intermodal transportation infrastructure is used to handle freight significantly affects transportation costs and service times. As a result, one of the most important decisions in intermodal freight transportation planning is the design of its logistics network. An intermodal logistics network is formed by the collection of hubs (i.e., physical locations) which are used for the transfer of freight loads from one transportation mode to another; and, the connections between hubs based on the transportation modes that are available at each node.

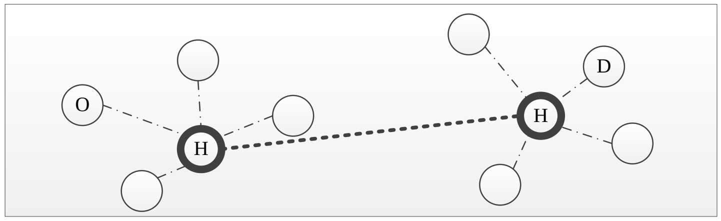
The intermodal logistics network design problem is a strategic planning problem that determines the number of hubs needed, their locations, and the allocation of non-hub nodes to hubs. However, this problem is not independent of other decisions that are made at different levels of decision making which affect hub locations and are also affected by them at the same time. For example, resource levels at hubs, terminal layout, and type and number of material handling and storage equipment are determined at the tactical level, while the selection of routes and mode of transportation for shipments are determined at the operational level. However, all of these tactical and operational decisions greatly depend on the configuration of the hub network. These decisions should be handled together as much as possible to minimize the total cost of the intermodal logistics network or to maximize the level of customer satisfaction. In the current research, the hub location problem has been integrated with the route and mode selection problems to find an optimal intermodal logistics network design by developing a path-based formulation which is then solved using a decomposition-based approach.

Network operators at large logistics companies such as Class I railroads and large full truckload carriers providing intermodal service are the potential decision makers who would be affected by the current research. Network operators make the strategic decisions of determining the network topology and designing the logistics network for intermodal transportation (Macharis and Bontekoning, 2004).

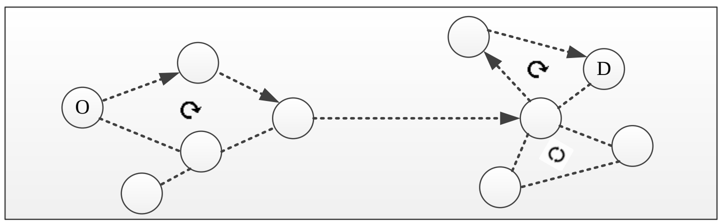
Various network topologies have been implemented for intermodal transportation including point to point, corridor, hub and spoke, connected hubs, static routes, and dynamic routes (Woxenius, 2007). This research considers a hybrid network topology that combines the point to point, connected hubs and static routes topologies as alternatives for intermodal freight transportation service (Figure 3.1). Therefore, the problem studied in this research is not a traditional hub-and-spoke network design problem, but one in which any pair of nodes can be connected with a direct link and there is no restriction that loads must visit one or at most two hubs in a route. In this way, all hubs are directly connected with each other and freight might visit multiple hubs in its route from origin to destination. Nodes in a network may represent physical locations where single mode terminals exist or where intermodal hubs can be potentially installed, as well as customer locations. In this way, network planners can address problems at different levels of aggregation from regional networks, to national and even international networks.



(a) Point to Point



(b) Connected Hubs



(c) Static Routes

Figure 3.1. This research considers a hybrid network topology that combines point to point, connected hubs and static routes topologies (adapted from Woxenius (2007)).

In practice, intermodal logistics networks usually have many nodes and origin-destination (O-D) pairs with freight demand. Therefore, previous mathematical formulations for intermodal logistics network design have many decision variables and constraints that make those formulations intractable for large size networks, even when no other decisions are integrated. To overcome this challenge and be able to integrate tactical decisions in the network design problem, a composite variable formulation was developed in which the complete route for a load from origin to destination was considered as a single composite variable used in a mixed integer linear programming (MILP) formulation of this problem. Moreover, composite variables allow enforcing some of the operational constraints implicitly at the same time feasible routes are being generated instead of adding those constraints to the MILP model. The combination of this formulation and the solution approach developed in this research allows us to obtain exact solutions for non-trivial instances (up to 150 nodes) in reasonable computation times. Therefore, the developed model and proposed solution approach provide a contribution in terms of being able to obtain exact solutions for larger problem instances than those that have been approximately solved in the existing literature.

The rest of this chapter is organized as follows. A review of previous studies in intermodal logistics network design is presented in Section 3.3. In Section 3.4, we define the problem under study and introduce the mathematical formulation and solution approach developed in this research. Computational test results are presented in Section 3.5. Finally, concluding remarks and future research directions are presented in Section 3.6.

3.3 Literature Review

Research on intermodal transportation planning has increased significantly in the last decade (SteadieSeifi et al., 2014). One of the important research problems studied in this area has been the optimal design of the logistics network for intermodal transportation. Hub and spoke networks have been studied the most in previous research related to intermodal transportation (SteadieSeifi et al., 2014). Although a wide variety of research studies have been conducted in the design of hub-based networks for other transportation systems (e.g., air transportation, less-than-truckload trucking, express package shipping, etc.), intermodal freight transportation has its own characteristics and restrictions that should be explicitly considered when designing its logistics network. Comprehensive reviews of research studies in the design of hub-based networks for different applications can be found in Alumur and Kara (2008), Campbell and O'Kelly (2012), and Farahani et al. (2013).

From the previous literature, operations research techniques have been commonly used to design intermodal logistics networks. In most cases, the design problem has been modeled using a mathematical program, and either heuristic or metaheuristic approaches have been developed to obtain solutions for large size instances. The intermodal hub network design problem was initially modeled using mathematical programming by Arnold et al. (2001) and Arnold et al. (2004). Another early mathematical model was developed by Racunica and Wynter (2005). Later, Rahimi et al. (2008) used a location-allocation formulation to find the optimal number and location of inland ports in an intermodal logistics network in the state of California. The authors considered the minimization of total facility and transportation costs as the objective function of their proposed MILP model. In another study, Limbourg and Jourquin (2009) modeled the hub location problem for intermodal transportation as a *p*-hub median problem. In this mathematical model, each node can be allocated to only one hub. Then, the authors developed an iterative procedure which relaxes this constraint and tries to find the optimal hub locations among a set of potential hub locations.

Ishfaq and Sox (2011) developed a mathematical model based on the multiple-allocation *p*-hub median problem. In their proposed model, each load can only visit up to two hubs in its movement from origin to destination. Also, economies of scale due to transshipments at hubs are accounted for by multiplying the inter-hub transportation cost by a constant discount factor. The authors implemented a tabu search (TS) algorithm to find near optimal hub locations which were compared to lower bounds obtained using a Lagrangian relaxation approach. Later, Ishfaq and Sox (2012) extended their original hub location problem formulation to enforce limitations on terminal resource levels by modeling the hub operations as a G/G/1 queuing system and estimate transitioning time for loads more accurately. The authors developed a mixed integer nonlinear mathematical model and implemented a TS approach to find near optimal hub locations and the allocation of spokes to hubs that minimizes the total network costs including the fixed cost of opening hubs, the cost of adapting them to different transportation modes, and transportation and service costs.

Using a different approach, Sörensen et al. (2012) developed a couple of two-stage solution approaches for the mathematical model previously developed by Arnold et al. (2001). The authors considered a MILP model which allows point to point transportation as well as using at most two hubs for transporting each freight load. Near optimal hub location-allocations were determined such that the total transportation cost was minimized. In each solution approach, the first stage deals with the construction of an initial solution, and the second stage improves the initial solution based on a local search. More recently, Sörensen and Vanovermeire (2013) extended the original formulation of Sörensen et al. (2012) to consider a bi-objective mathematical model in which all the assumptions previously considered remain the same. The first objective function minimizes the total transportation cost while the second objective function minimizes the total hub installation cost. The authors approximated the optimal Pareto set by applying a problem-specific greedy randomized adaptive search (GRASP) procedure.

At the same time, Alumur et al. (2012a) and Alumur et al. (2012b) proposed mathematical formulations for hub network design problems considering delivery due date constraints and multiple transportation modes. Alumur et al. (2012a) focused on single allocation hub network design problems, while Alumur et al. (2012b) studied the hierarchical hub median problem. In the latter, a MILP model was developed which was solved by taking advantage of variable fixing rules and valid inequalities.

Finally, in contrast to most previous research studies that consider the minimization of total transportation and installation costs as the criteria for intermodal logistics networks design optimization, a few recent studies consider the minimization of environmental effects associated with intermodal freight transportation. For example, Zhang et al. (2013) developed a mathematical model that minimizes the cost of CO_2 emissions associated with each shipment in the network. The authors implemented a GA to find a near optimal solution for the configuration of a terminal network for intermodal transportation in a real application in the Netherlands. Also, Qu et al. (2016) developed a nonlinear integer programming model for intermodal network design that considers the cost of greenhouse gas emissions. The authors linearized the proposed model and solved it for a real case study with eleven locations in the United Kingdom. Finally, the authors showed that the developed model can be easily modified into a bi-objective mathematical model.

Comprehensive reviews of research studies in strategic intermodal transportation planning can be found in Macharis and Bontekoning (2004), Caris et al. (2013), and SteadieSeifi et al. (2014). A summary of the previous literature presented in this review is presented in Table 3.1.

Table 3.1. Summary of previous research on intermodal logistics network design.

Reference	Objective	Modeling Approach	Solution Approach	Consolidation Effect on Transportation Cost
Rahimi et al. (2008)	Total Cost Minimization	Single Facility Location	Exact (6 nodes)	N/A
Limbourg & Jourquin (2009)	Transportation Cost Minimization	Multiple Allocation p-Hub Median	Exact (Hub Location Only) Metaheuristic (Complete Model)	Constant Discount Factor
Ishfaq & Sox (2011)	Total Cost Minimization	Single Allocation p-Hub Median	Tabu Search	Constant Discount Factor
Ishfaq & Sox (2012)	Total Cost Minimization	Nonlinear Mixed Integer Programming	Tabu Search	Constant Discount Factor
Sörensen et al. (2012)	Total Cost Minimization	Mixed Integer Programming	Metaheuristic	N/A
Sörensen et al. (2013)	Total Cost Minimization	Bi-objective Mixed Integer Programming	GRASP	N/A
Zhang et al. (2013)	CO_2 Emissions Cost Minimization	Mixed Integer Programming	GA	N/A
Qu et al. (2014)	Greenhouse Gas Emissions Cost Minimization	Nonlinear Integer Programming	Exact (11 Nodes)	N/A
Current Research	Total Cost Minimization	Integer Programming using CVs	Decomposition Approach	Constant Discount Factor

Like most previous studies, this research attempts to minimize the total transportation and fixed facility installation costs. However, the modeling approach integrates the load route and transportation mode selection problems within the hub location problem using a composite variable (CV) formulation. Also, from a network topology perspective, while most of the existing literature focuses on designing intermodal logistics networks that are based on the hub and spoke model, this research considers a hybrid network topology that combines point to point, connected hubs and static routes topologies. Moreover, while all previous studies have focused on heuristic solution methods, the composite variable formulation and the decomposition algorithm that are presented in this research can be used to obtain optimal solutions for non-trivial instances (with up to 150 nodes).

3.4 Methodology

3.4.1 Problem Definition

The Integrated Intermodal Logistics Network Design (IILND) problem can be defined as determining in an integrated manner the location of hubs, routes for loads, and their transportation mode in an intermodal freight transportation network. The objective is to minimize the total network cost which includes the fixed cost of hub installation and the variable transportation cost. Network operators at large motor carriers and Class I railroads providing intermodal freight transportation service would benefit from being able to address these problems concurrently and avoid sub-optimality of solutions obtained using a multi-stage approach.

An intermodal logistics network consists of *N* nodes. Nodes can be the origin or destination of loads or serve as hubs. Note that although intermodal shipments can visit one or more hubs from origin to destination, point to point movements (i.e., without visiting any hub) can also be selected to form the hybrid network configuration that we consider in this research. The size of an instance will be determined by the level of aggregation considered when planning the intermodal logistics network going from regional to national or even international networks. Most of the time, loads are picked up at their origin node by trucks and moved to predetermined hub nodes before reaching their final destination. At the hub nodes, loads are sorted and consolidated based on their destination, and any necessary transition to a different transportation mode is completed. When a transportation mode decision is made, the split of loads follows an All-Or-Nothing assignment policy where the complete shipment is transported using the same mode.

The purpose of consolidating different loads at the hub nodes is to reduce the transportation cost by taking advantage of economies of scale. In other words, by consolidating different loads at the hub nodes, fewer resources are needed to transport loads between hubs and the transportation cost per load decreases. On the other hand, consolidating loads and transferring them to different transportation modes takes time which increases the total transportation time for a particular load between origin and destination. Consequently, as more hub nodes are visited by a load, the total transportation time increases. Thus, loads with small transportation time windows should not be routed through multiple hub nodes even if the total transportation cost is reduced. Note that all containers of a given load should have the same maximum allowed transportation time. For this reason, containers carrying freight with the same origin and destination, but different maximum allowed transportation times should be considered as different loads. Also note that although a time restriction for load delivery would be more important at the operational planning level, we still incorporated one in the integrated problem to be able to provide a service guarantee to customers based on the design of the network. From a modeling perspective, similar to some of the previous studies, the consolidation effect on transportation costs and times for inter-hub movements is modeled using constant discount and delay factors, respectively.

In this research, only a subset P of the N nodes is allowed to serve as potential hub nodes. Among these potential hub nodes, V locations are selected for installation of hub facilities. There is a fixed cost associated with the installation of a hub facility which differs from one node to another. Also, demand in this network consists of L different loads; each load is characterized by its origin location, destination location, quantity of containers, and maximum allowed transportation time. The total time it takes to move a load from its origin to its destination including the transit time and the time it spends at hub nodes should be less than the maximum allowed transportation time for that particular load.

3.4.2 Mathematical Formulation

The IILND problem is modeled using a composite variable formulation in which a complete feasible route from origin to destination is considered as a single variable. These routes can connect origin to destination directly using a single transportation mode or visit as many hubs as needed with as many transitions between different modes as necessary. However in all of the completed experiments presented below in Section 4, the number of hub nodes that each load can visit is always restricted to be at most two. This is a reasonable limitation for small and medium size networks and even, in some cases, large intermodal logistics networks. The following subsections present the notation, composite variable definition and generation method, and the proposed mathematical programming formulation of the IILND problem.

3.4.2.1 Notation

Sets and Parameters

N	set of nodes n,
P	set of potential hub nodes n, $P \subset N$,
M	set of transportation modes m,
L	set of loads l,
V	number of hubs in a feasible hub combination,
H	set of hub combinations h, each hub combination consists of V nodes corresponding to hub locations,
$R_{l,h}$	set of composite variables (i.e. feasible routes) i to transport load l when hubs in hub combination h are open,
TW_l	maximum allowed transportation time for load l,
F_h	fixed cost of hub installation for hub combination h,
d_l	demand quantity (in number of containers) for load l,
$C_{l,i}^h$	per load transportation cost of moving load l on route i when hubs in hub combination h are open,
$t_{l,i}^h$	time to transport load l on route i when hubs in hub combination h are open,

Decision Variables

$$r_{l,i}^h = \begin{cases} 1 & \text{if feasible route } i \text{ is selected to transport load } l \text{ using hub combination } h \\ 0 & \text{otherwise,} \end{cases}$$

$$Y_h = \begin{cases} 1 & \text{if hubs in hub combination } h \text{ are open} \\ 0 & \text{otherwise.} \end{cases}$$

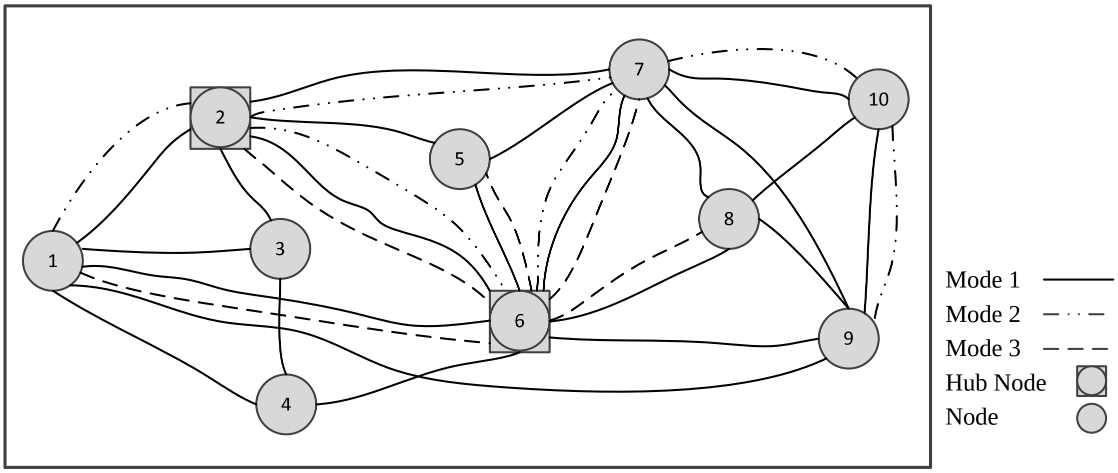
3.4.2.2 Composite Variable Definition and Generation Method

A single composite variable, denoted $r_{l,i}^{h}$, is defined as a feasible route *i* used to transport load *l* from origin to destination when hubs in hub combination *h* are open. The feasibility of a route is determined by the number of hubs visited and the limitation on the transportation time from origin to destination for a given load. In the former case, a feasible route can directly connect origin to destination for a load or visit as many hubs as the number of hubs that are open in a hub combination. In the latter case, the total transportation time for a route cannot exceed the maximum allowed transportation time for the corresponding load.

With this composite variable definition, the sets of feasible routes to transport each load for a given hub combination need to be generated to formulate a mathematical model for IILND. Similarly, values need to be calculated for parameters such as the fixed cost of a given hub combination, F_h, and the transportation cost and the transportation time for a feasible route, $C_{l,i}^{h}$ and $t_{l,i}^{h}$, respectively.

To generate the set of feasible routes *i* to transport load *l* when hubs in hub combination *h* are open, $R_{l,h}$, all time feasible routes from origin to destination need to be enumerated. Note that if two routes visit the same sequence of nodes but use different transportation modes in at least one of their transportation legs, they are considered to be two different composite variables. For example, Figure 3.2 shows all feasible routes to transport a load from node 1 to node 9 when hubs are open at nodes 2 and 6. As shown in Figure 3.2, the second and third composite variables visit the same nodes but use different transportation modes to move the freight between node 1 and node 6. Therefore, selecting a composite variable for a particular load in the optimal solution means selecting the optimal route and optimal transportation mode for that load.

As composite variables for a given load and given hub combination are generated using exhaustive enumeration, the transportation time for a route can be compared to the maximum allowed transportation time of the corresponding load. In that way, routes that violate the maximum allowed transportation time constraint can be discarded. As a result, the maximum allowed transportation time constraint does not need to be included in the mathematical formulation of IILND problem.



Set of feasible routes *i* to transport load *l* (origin = 1, destination = 9) when hubs at nodes 2 and 6 are open:
(*i* = 1): 1 – (Mode 1) → 9
(*i* = 2): 1 – (Mode 1) → 6 – (Mode 1) → 9
(*i* = 3): 1 – (Mode 3) → 6 – (Mode 1) → 9
(*i* = 4): 1 – (Mode 1) → 2 – (Mode 1) → 6 – (Mode 1) → 9
(*i* = 5): 1 – (Mode 1) → 2 – (Mode 2) → 6 – (Mode 1) → 9
(*i* = 6): 1 – (Mode 1) → 2 – (Mode 3) → 6 – (Mode 1) → 9
(*i* = 7): 1 – (Mode 2) → 2 – (Mode 1) → 6 – (Mode 1) → 9
(*i* = 8): 1 – (Mode 2) → 2 – (Mode 2) → 6 – (Mode 1) → 9
(*i* = 9): 1 – (Mode 2) → 2 – (Mode 3) → 6 – (Mode 1) → 9

Figure 3.2. Set of feasible routes *i* to transport load *l* (origin = 1, destination = 9) when hubs at nodes 2 and 6 are open.

In the determination of the transportation time and cost for a route, two additional parameters are required for modeling the influence of the operations completed at hub nodes. First, inter-hub transportation times should be multiplied by a constant delay factor β that is greater than one to account for delays that occur at the hubs (i.e., an operation delay factor β = 1.25 represents an additional 25% time in the movement of a load between two hubs). Similarly, all inter-hub transportation costs should be multiplied by a constant discount factor α that is less than one to account for economies of scale (i.e., a discount factor α = 0.75 represents a reduction of 25% in the transportation cost between two hubs). These two parameters could be estimated from past data or they could be set based on expert opinion.

3.4.2.3 Mathematical Formulation

Using the notation and the composite variable definition presented above, the mathematical programming formulation for the IILND problem follows:

$$Minimize \sum_{h}^{H} F_h Y_h + \sum_{h}^{H}\sum_{l}^{L}\sum_{i}^{R_{l,h}} C_{l,i}^{h}.\, d_l.\, r_{l,i}^{h} \tag{3.1}$$

Subject to:

$$\sum_{l}^{L}\sum_{i}^{R_{l,h}} r_{l,i}^{h} \leq |L| Y_h \qquad \forall h \in H \tag{3.2}$$

$$\sum_{h}^{H}\sum_{i}^{R_{l,h}} r_{l,i}^{h} = 1 \qquad \forall l \in L \tag{3.3}$$

$$\sum_{h}^{H} Y_h = 1 \tag{3.4}$$

$$Y_h = \{0,1\} \qquad \forall h \in H \tag{3.5}$$

$$r_{l,i}^{h} = \{0,1\} \qquad \forall l \in L, \forall i \in R_{l,h}, \forall h \in H \tag{3.6}$$

The objective function (3.1) minimizes total network cost consisting of the fixed cost of hub installation and the transportation costs. The objective function (3.1) does not include operation costs related to handling of freight at hubs. Constraint (3.2) enforces that hub terminals can be used only if they are open, however no real capacity constraint for hubs was considered in the model and only and upper bound was set equal to the total number of loads L. Constraint (3.3) requires that all demand should be satisfied. Constraint (3.4) enforces that only one hub combination can be selected. And, finally, constraints (3.5) and (3.6) are the variable type constraints.

3.4.3 Solution Approach

The mathematical programming formulation presented in Section 3.4.2.3 has two sets of decision variables, one for determining the hub locations (Y_h) which is a strategic decision, and one for selecting the optimal routes and transportation mode for each load ($r_{l,i}^{h}$) which are tactical decisions. The general idea behind the proposed solution approach is to use a decomposition approach with a master problem and a sub-problem as illustrated in Figure 3.3. The master problem searches through the feasible region of all hub combinations using exhaustive enumeration, and uses the sub-problem to find optimal load routes and transportation modes to evaluate hub locations.

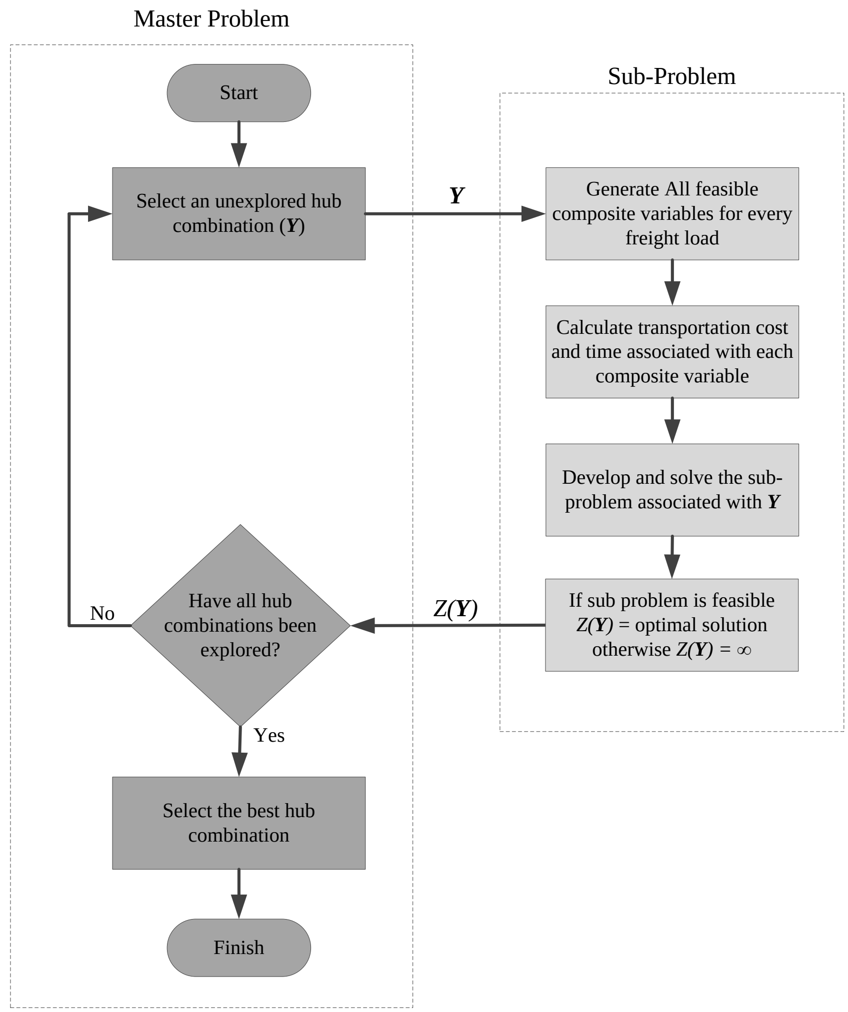


Figure 3.3. Flowchart of the decomposition solution approach.

Note that the two sets of decision variables included in the mathematical model for IILND are not independent and are linked by constraint (3.2) (i.e., the feasible routes vary for each hub combination). For example, consider the 10-node network illustrated in Figure 3.3 and that two hub locations are required. In this case, there are $\binom{10}{2} = 45$ hub combinations, and each one of them represents a solution to the hub location problem. Two different 2-hub combinations are shown in Figure 3.4 to show how the two sets of decision variables (Y_h and $r_{l,i}^{h}$) are related to each other. Note that *hub combination 1* is associated with the solution in which hubs are open at nodes 2 and 6, while *hub combination 2* is associated with the solution in which hubs are open at nodes 6 and 7. The feasible routes to transport a load from node 1 to node 9 vary if *hub combination 1* is selected instead of *hub combination 2*. The sets of feasible routes are included in Figure 3.4, however only one of the feasible routes is illustrated for each case.

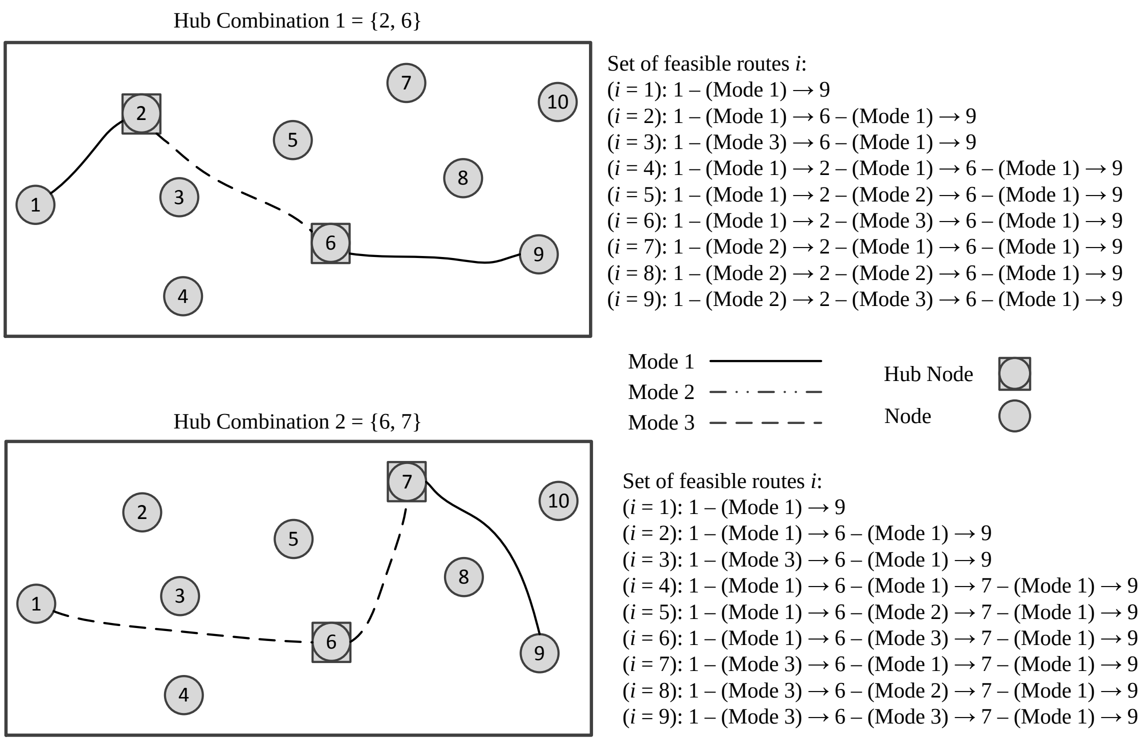


Figure 3.4. Feasible routes for a load between nodes 1 and 9 in a 10 node network for two different hub combinations.

3.4.3.1 Two-Stage Optimization Approach

The special structure of the proposed mathematical model allows the implementation of a two-stage optimization approach in which for each hub combination, the selection of the optimal load routes and transportation modes are determined. The resulting optimal transportation cost is then used to evaluate the corresponding hub combination. A decomposition approach is used because all of the constraints in the mathematical formulation of IILND presented in Section 3.4.2.3 contain only one of the two decision variables with the exception of constraint (3.2).

Considering a hub combination *h*, the selection of the optimal load route and transportation mode for each load can be determined by solving the following sub-problem:

<u>Sub-Problem</u>

$$SP(r|\widehat{\boldsymbol{Y}}) = Minimize \sum_{l}^{L}\sum_{i}^{R_{l,h}} C_{l,i}^{h}.d_{l}.r_{l,i}^{h} \qquad (3.7)$$

Subject to:

$$\sum_{i}^{R_{l,h}} r_{l,i}^{h} = 1 \qquad \forall l \in L \qquad (3.8)$$

$$r_{l,i}^{h} = \{0,1\} \qquad \forall l \in L, \forall i \in R_{l,h} \qquad (3.9)$$

The sub-problem $SP(r|\widehat{\boldsymbol{Y}})$ can further be separated into multiple sub-problems $SP_l(r|\widehat{\boldsymbol{Y}})$, one for each load $l \epsilon L$ for the given hub combination. The optimal solution for $SP_l(r|\widehat{\boldsymbol{Y}})$ can be easily found just after all composite variables have been generated by choosing the feasible route that has the minimum transportation cost.

Now, let $\widehat{\boldsymbol{Y}}$ be a vector of all possible hub combinations Y_h, and $Z_l(\widehat{\boldsymbol{Y}})$ be the optimal transportation cost for the sub-problem presented above. Suppose that $Z_l(\widehat{\boldsymbol{Y}}) = \infty$ if the sub-problem associated with $\boldsymbol{Y}$ is infeasible. The following master problem (MP) can be used to find an optimal hub combination.

Master Problem

$$Minimize \sum_{h}^{H} F_h Y_h + \sum_{l}^{L} Z_l(\widehat{\boldsymbol{Y}}) \tag{3.10}$$

Subject to:

$$\sum_{h}^{H} Y_h = 1 \tag{3.11}$$

$$Y_h = \{0,1\} \qquad \forall h \in H \tag{3.12}$$

To solve the master problem, all possible hub combinations need to be enumerated. There are $\binom{|P|}{V}$ hub combinations and enumerating all of them could be time consuming. To avoid exhaustive enumeration and obtaining the optimal solution faster, a search algorithm is developed.

3.4.3.2 Search Algorithm

A search algorithm was developed that utilizes an upper bound on the optimal solution of the MP to discard a portion of hub combinations from exploration. The upper bound is obtained by evaluating the total network costs including the fixed hub installation costs and the transportation costs associated with a given hub combination. Hub combinations with fixed installation costs greater than the current upper bound can be discarded from exploration.

Moreover, for hub combinations that are not previously discarded, the optimal solution of each sub-problem can be added to the total network cost as the sub-problems are solved. In this way, a hub combination can be discarded whenever its total network cost exceeds the upper bound before all sub-problems have been solved. Also, in order to evaluate the solutions of the MP even faster, loads can be ordered according to their demand and their O-D distance, so the sub-problem associated with a load with the largest product of demand times O-D distance is solved first. Note that this sub-problem is expected to have a large objective function value. As a result, the likelihood of eliminating non-optimal hub combinations after solving fewer sub-problems is higher.

The upper bound can be updated whenever a better solution is found for the MP. The pseudo code of this search algorithm is presented in Figure 3.5.

```
Sort set of loads according to Demand(l)×Distance(origin(l),destination(l))
UB = ∞
for hub combination h ϵ set of all hub combinations
        total cost (h) = the fixed installation cost associated with h
                if total cost (h) > UB
                        Discard h
                for load l ϵ set of sorted loads
                        formulate SP_l(r|Y)
                        Z_l(Y) = optimal transportation cost (SP_l(r|Y))
                        total cost (h) = total cost (h) + Z_l(Y)
                        if total cost (h) > UB
                                Discard h
        if total cost (h) < UB
                UB = total cost (h)
                Optimal hub combination = h
Return optimal hub combination
```

Figure 3.5. Pseudo code of the search algorithm.

Preliminary computational experiments showed that for non-trivial size networks (i.e., a network with 150 nodes and 4,500 loads), the optimal solution can be obtained in reasonable computational times. A detailed discussion on computational experiments is presented in Section 3.5.

3.5 Computational Experiments

3.5.1 Experimental Design

Two sets of experiments were completed to evaluate the performance of the proposed mathematical model and solution approach. The performance metrics analyzed were selected to analyze the configuration of the solutions obtained and the computational time required to obtain solutions. In the first set of experiments (Set A), three complete networks (i.e., networks were all pairs of nodes are connected to each other) of sizes 10, 20 and 30 nodes were randomly generated. All nodes were considered as part of the set of potential hubs *P* (i.e., the set of all potential hub nodes *P* is equal to the set of all nodes *N*). In the second set of experiments (Set B), four complete networks of size 50, 75, 100 and 150 were randomly generated. Unlike Set A, the set of potential hub locations was considered to consist only of 10%, 15% and 20% of all nodes for the networks generated in Set B. Nodes in each network were uniformly distributed in a 1 x 0.5 rectangular area for both sets of experiments.

Regarding cost information, the fixed cost of hub installation at a node was generated using a uniformly distributed random variable between 4,000 and 5,500. On the other hand, transportation cost per load and the time it takes to move loads between nodes *i* and *j* depend on the transportation mode and the distance between *i* and *j* according to equations (3.13) to (3.18) below. The distance between origin and destination has a significant role in per load transportation cost and transportation time, but transportation costs are not completely proportional to O-D distance as there are other cost sources other than fuel prices such as the time value tied to goods in transit, maintenance costs, and environmental costs including local and global air pollution, congestion, noise pollution, and traffic accidents (Janic, 2007). As a result, the triangular inequality does not hold in real world problems. In the completed experiments, random values between 0 and 1 have been added to equations (3.13) to (3.18) to model the situation that the triangle inequality does not hold in any of the instances. In these equations, *Random*(0,1) is a uniformly distributed random variable between 0 and 1. Note that in all experiments it is assumed that the utilization of all transportation modes is high, so a higher numbered transportation mode represents a mode that is more time consuming but provides a less expensive per load transportation cost over long distances.

Mode (m)	**Transportation cost per load between nodes *i* and *j* using mode *m* (C_{ij}^{m})**	
1	$C_{ij}^{1} = Distance\ (i,j)\ /\ 2\ +\ Random(0,1)$	(3.13)
2	$C_{ij}^{2} = Distance\ (i,j)\ /\ 3\ +\ Random(0,1)$	(3.14)
3	$C_{ij}^{3} = Distance\ (i,j)\ /\ 4\ +\ Random(0,1)$	(3.15)

Mode (m)	**Time to move a load between nodes *i* and *j* using mode *m* (t_{ij}^m)**	
1	$t_{ij}^1 = Distance\ (i,j) + Random(0,1)$	(3.16)
2	$t_{ij}^2 = Distance\ (i,j) \times 1.5 + Random(0,1)$	(3.17)
3	$t_{ij}^3 = Distance\ (i,j) \times 2 + Random(0,1)$	(3.18)

For each network, L different loads were randomly generated. Demand for each load was a uniformly distributed random value between 50 and 150. In Set A experiments, the value of L was set to be equivalent to 5%, 10%, 20% and 50% of all possible O-D pairs in the complete network. While in Set B experiments, the value of L is equal to 20% of all possible O-D pairs in the complete network. Five different sets of loads were generated for each value of L.

The maximum allowed transportation time for a load was a random uniformly distributed value between 2 and 6 time units, while the operation delay factor (β) was set to 1.2. Different values for discount factor (α), number of modes (T), number of hubs (V), and number of potential hub locations were considered in solving all instances. The values used for the discount factor (α) and the delay factor (β) were set equal to values previously used in Ishfaq and Sox (2011). The list of all parameters and their values used in our computational experiments are shown in Table 3.2.

Table 3.2. Computational experiment parameters and their values.

Parameter	**Set A**	**Set B**
Number of Nodes (N)	10, 20, 30	50, 75, 100, 150
Number of Loads (L)	5%, 10%, 20% and 50% of all possible O-D pairs	20% of all possible O-D pairs
Number of Hubs (V)	2, 3, 4	2, 4
Number of Modes (T)	2, 3	2, 3
Discount Factor (α)	0.5, 0.9	0.5
Number of Potential Hub Locations	100% of all nodes	10%, 15% and 20% of all nodes

In all of the completed experiments it was assumed that each load can visit up to two hubs and the drayage operation can only be handled by trucks. Note that these two restrictions are not imposed by the mathematical formulation or the solution approach, but they were assumed as they are common limitations in most real world instances.

3.5.2 Computational Results

The solution approach presented in Section 3.4.3 was implemented in MATLAB, and all computational experiments were run on a 2.83 GHz Quad Core computer with 8 GB of RAM. All instances in both Set A and Set B experiments were solved to optimality using both an exhaustive enumeration approach and the proposed search algorithm described in Section 3.4.3.2.

3.5.2.1 Set A Computational Results

In addition to applying exhaustive enumeration and the proposed search algorithm, smaller instances of Set A were solved using CPLEX 12.2 to assess the performance of the search algorithm. Solutions obtained with the proposed search algorithm were optimal in all cases when compared to the solutions obtained with exhaustive enumeration and CPLEX.

We first present trends observed in optimal solution costs for different experimental treatment combinations, and then compare the computational performance of the search algorithm with respect to the other two methods. Table 3.3 shows the optimal solution costs for different experimental treatment combinations for one instance (i.e., Network Instance 1). The trends observed in Table 3.3 are representative of all instances that were tested.

Table 3.3. Optimal solution costs for Network Instance 1 (Set A).

# of Nodes	# of Loads	Criteria	# of Modes = 2						# of Modes = 3					
			Discount Factor = 0.5			Discount Factor = 0.9			Discount Factor = 0.5			Discount Factor = 0.9		
			V = 2	V = 3	V = 4	V = 2	V = 3	V = 4	V = 2	V = 3	V = 4	V = 2	V = 3	V = 4
10	**5 (5%)**	Total Cost	8,520	12,812	17,198	8,530	12,847	17,233	8,521	12,812	17,199	8,531	12,847	17,234
		% Fixed Cost	98	99	99	98	98	99	98	99	99	98	98	99
	9 (10%)	Total Cost	8,767	13,066	17,452	8,781	13,090	17,458	8,767	13,066	17,446	8,781	13,090	17,446
		% Fixed Cost	95	97	98	95	97	98	95	97	98	95	97	98
	18 (20%)	Total Cost	9,395	13,699	18,030	9,425	13,732	18,095	9,395	13,685	18,005	9,423	13,712	18,065
		% Fixed Cost	89	92	94	88	92	94	89	92	95	88	92	94
	45 (50%)	Total Cost	11,284	15,432	19,677	11,448	15,652	19,994	11,284	15,409	19,647	11,430	15,606	19,941
		% Fixed Cost	74	82	87	73	81	85	74	82	87	73	81	85
20	**19 (5%)**	Total Cost	9,476	13,773	18,135	9,515	13,806	18,183	9,476	13,773	18,135	9,489	13,806	18,183
		% Fixed Cost	88	93	95	88	93	95	88	93	95	88	93	95
	38 (10%)	Total Cost	11,214	15,436	19,667	11,234	15,495	19,813	11,214	15,412	19,643	11,234	15,483	19,733
		% Fixed Cost	76	84	87	75	83	87	76	84	88	75	83	87
	76 (20%)	Total Cost	13,647	17,731	21,862	13,682	17,843	22,024	13,647	17,690	21,789	13,682	17,735	21,907
		% Fixed Cost	61	72	79	62	72	78	61	73	79	62	73	79
	190 (50%)	Total Cost	20,263	23,912	27,722	20,387	24,316	28,430	20,199	23,836	27,632	20,387	24,182	28,192
		% Fixed Cost	44	54	63	42	53	61	45	54	63	42	53	62
30	**44 (5%)**	Total Cost	11,101	15,095	19,251	11,126	15,136	19,314	11,101	15,095	19,251	11,117	15,136	19,305
		% Fixed Cost	75	83	88	75	83	86	75	83	88	74	83	86
	87 (10%)	Total Cost	14,089	18,164	22,220	14,126	18,281	22,425	14,089	18,150	22,206	14,110	18,255	22,400
		% Fixed Cost	58	68	75	58	68	76	58	68	75	58	68	74
	174 (20%)	Total Cost	20,003	23,753	27,615	20,134	23,937	27,884	19,987	23,753	27,615	20,058	23,932	27,881
		% Fixed Cost	41	53	61	41	52	61	43	53	61	43	52	61
	435 (50%)	Total Cost	35,159	38,376	41,580	35,390	38,657	42,272	35,152	38,308	41,506	35,383	38,657	42,193
		% Fixed Cost	27	36	44	26	36	43	27	36	44	26	36	43

Note that in Table 3.3, the number of hubs to locate was predetermined and the optimal solution cost was obtained. Solutions for different number of open hubs should be obtained and compared if the optimal number of hubs to open is of the interest. According to Table 3.3, the optimal number of open hubs depends on the number of loads for a fixed network size. For a small number of loads, opening more hubs increased the fixed cost of hub installation, but only slightly reduced the transportation cost. So, the optimal number of open hubs was relatively small. On the other hand, if the number of loads was relatively large, opening more hubs reduced the transportation cost significantly as compared to the additional fixed cost of building more hubs.

Also, according to Table 3.3, the solution cost when three transportation modes were considered was always less than or equal to the solution cost when two transportation modes were considered showing the benefit of having more flexibility for transporting loads in alternative modes from origin to destination.
Regarding the effect of the discount factor α, it was observed that the solution cost always increased when the discount factor was changed from 0.5 to 0.9 (i.e., from a 50% discount to a 10% discount).

The delay factor β was not changed in any of the experiments, but it is expected that by increasing β, the delays that occur at hubs would increase which means that the total transportation time would increase. This might result in some routes being infeasible with respect to the maximum allowed transportation time constraint. As a result, increasing β will not improve the optimal solution, but it can worsen it. On the other hand, decreasing the delay factor β could improve the value of the objective function.

Regarding the computational performance of the proposed search algorithm, average solution times over multiple instances for the same experimental treatment combination were computed and are presented in Table 3.4 and Table 3.5. Table 3.4 shows the average solution times for small Set A instances solved with CPLEX and the search algorithm. Note that for some experimental treatment combinations, the optimal solution was not obtained using CPLEX due to the large number of decision variables and constraints and the limited amount of CPU memory. These experimental treatment combinations are marked with an X in Table 3.4.

Table 3.4. Set A average solution times (in seconds) with CPLEX and search algorithm.

# of Nodes	# of Loads	Approach	# of Modes = 2						# of Modes = 3					
			Discount factor = 0.5			Discount factor = 0.9			Discount factor = 0.5			Discount factor = 0.9		
			# of Hubs			# of Hubs			# of Hubs			# of Hubs		
			2	3	4	2	3	4	2	3	4	2	3	4
10	5	CPLEX	2.227	33.560	345.659	2.231	33.392	345.609	2.968	59.678	758.789	2.855	56.059	761.144
		SA	0.006	0.003	0.003	0.000	0.000	0.006	0.003	0.006	0.006	0.000	0.006	0.003
	9	CPLEX	4.232	84.280	1,357.037	4.243	83.094	1,370.157	5.339	140.483	2,741.078*	5.339	142.070	2,792.047*
		SA	0.000	0.000	0.006	0.003	0.003	0.006	0.000	0.006	0.006	0.006	0.003	0.006
	18	CPLEX	15.171	583.311	X	15.261	587.937	X	21.606	1,472.003	X	21.614	1,473.671	X
		SA	0.003	0.003	0.009	0.003	0.016	0.019	0.003	0.009	0.016	0.009	0.012	0.022
	45	CPLEX	92.052	X	X	90.933	X	X	139.508	X	X	X	X	X
		SA	0.016	0.044	0.081	0.016	0.037	0.087	0.019	0.050	0.090	0.016	0.047	0.106

* Average of 4 instances

Table 3.5. Set A average solution times (in seconds) with exhaustive enumeration and search algorithm (part a).

# of Nodes	# of Loads	Approach	# of Modes = 2						# of Modes = 3					
			Discount factor = 0.5			Discount factor = 0.9			Discount factor = 0.5			Discount factor = 0.9		
			# of Hubs			# of Hubs			# of Hubs			# of Hubs		
			2	3	4	2	3	4	2	3	4	2	3	4
10	5	Enum.	0.009	0.016	0.050	0.006	0.019	0.050	0.005	0.028	0.059	0.006	0.034	0.059
		SA	0.006	0.003	0.003	0.000	0.000	0.006	0.003	0.006	0.006	0.000	0.006	0.003
		%Diff.	-33	-80	-94	-100	-100	-88	-38	-78	-89	-100	-82	-95
	9	Enum.	0.009	0.019	0.059	0.009	0.025	0.059	0.009	0.028	0.078	0.003	0.031	0.081
		SA	0.000	0.000	0.006	0.003	0.003	0.006	0.000	0.006	0.006	0.006	0.003	0.006
		%Diff.	-100	-100	-89	-65	-88	-89	-100	-78	-92	100	-90	-92
	18	Enum.	0.005	0.037	0.075	0.006	0.037	0.081	0.009	0.041	0.097	0.015	0.037	0.103
		SA	0.003	0.003	0.009	0.003	0.016	0.019	0.003	0.009	0.016	0.009	0.012	0.022
		%Diff.	-38	-92	-88	-50	-58	-77	-67	-77	-84	-38	-67	-79
	45	Enum.	0.028	0.069	0.131	0.022	0.069	0.140	0.025	0.072	0.165	0.019	0.069	0.172
		SA	0.016	0.044	0.081	0.016	0.037	0.087	0.019	0.050	0.090	0.016	0.047	0.106
		%Diff.	-44	-36	-38	-29	-45	-38	-25	-30	-45	-17	-32	-38
20	19	Enum.	0.037	0.362	1.953	0.050	0.353	1.978	0.053	0.396	2.331	0.044	0.409	2.362
		SA	0.022	0.100	0.303	0.022	0.094	0.346	0.022	0.103	0.365	0.022	0.112	0.424
		%Diff.	-42	-72	-85	-56	-73	-82	-59	-74	-84	-50	-73	-82
	38	Enum.	0.087	0.555	3.011	0.078	0.558	2.973	0.090	0.624	3.479	0.087	0.615	3.516
		SA	0.053	0.328	1.285	0.053	0.328	1.379	0.062	0.362	1.541	0.056	0.381	1.650
		%Diff.	-39	-41	-57	-32	-41	-54	-31	-42	-56	-36	-38	-53
	76	Enum.	0.156	0.967	5.095	0.153	0.983	4.933	0.150	1.083	5.625	0.140	1.070	5.616
		SA	0.119	0.755	3.551	0.119	0.761	3.629	0.122	0.827	4.128	0.125	0.836	4.193
		%Diff.	-24	-22	-30	-22	-23	-26	-19	-24	-27	-11	-22	-25
	190	Enum.	0.337	2.237	10.99	0.328	2.209	11.21	0.346	2.493	12.73	0.346	2.505	12.78
		SA	0.300	1.909	9.285	0.293	1.925	9.354	0.303	2.031	10.49	0.303	2.090	10.61
		%Diff.	-11	-15	-16	-10	-13	-17	-13	-19	-18	-13	-17	-17

Table 3.6. Set A average solution times (in seconds) with exhaustive enumeration and search algorithm (part b).

# of Nodes	# of Loads	Approach	# of Modes = 2						# of Modes = 3					
			Discount factor = 0.5			Discount factor = 0.9			Discount factor = 0.5			Discount factor = 0.9		
			# of Hubs			# of Hubs			# of Hubs			# of Hubs		
			2	3	4	2	3	4	2	3	4	2	3	4
30	44	Enum.	0.209	2.321	19.32	0.218	2.331	19.15	0.225	2.590	22.31	0.222	2.590	22.27
		SA	0.156	1.289	7.438	0.150	1.342	8.071	0.150	1.445	8.880	0.153	1.498	9.550
		%Diff.	-25	-44	-62	-31	-42	-58	-33	-44	-60	-31	-42	-57
	87	Enum.	0.378	4.062	32.62	0.384	4.044	32.59	0.393	4.418	36.58	0.387	4.434	36.70
		SA	0.306	3.026	22.57	0.306	3.058	23.12	0.312	3.320	26.38	0.312	3.366	26.74
		%Diff.	-19	-25	-31	-20	-24	-29	-21	-25	-28	-19	-24	-27
	174	Enum.	0.724	7.482	58.87	0.711	7.385	58.31	0.721	7.912	66.09	0.721	7.984	66.29
		SA	0.612	6.187	47.47	0.608	6.234	47.97	0.627	6.686	54.19	0.627	6.699	54.41
		%Diff.	-16	-17	-19	-14	-16	-18	-13	-15	-18	-13	-16	-18
	435	Enum.	1.778	18.04	139.6	1.741	18.00	139.3	1.747	19.04	155.2	1.763	19.23	154.3
		SA	1.504	15.58	120.8	1.507	15.79	120.4	1.560	16.66	134.2	1.560	16.81	134.5
		%Diff.	-15	-14	-13	-13	-12	-14	-11	-13	-14	-12	-13	-13

According to Table 3.4, the average solution times for the search algorithm are significantly faster than the solution times observed with CPLEX. For example, the average solution time reduces from about 46 minutes with CPLEX to about 0.006 seconds with the search algorithm for instances with 10 nodes, 9 loads, and 4 open hubs. As the number of loads, open hubs, and transportation modes in the network increase, the number of decision variables and constraints in the mathematical formulation increase which results in longer CPLEX solution times.

Alternatively, Table 3.5 shows the average solution times observed for Set A instances using exhaustive enumeration and the search algorithm. Here, the exhaustive enumeration approach is used as a benchmark against the proposed search algorithm. According to Table 3.5, the average solution time for the search algorithm increased as the network size increased and the number of loads increased. The average solution time was also significantly affected by the number of open hubs. The minimum average solution time was a few milliseconds and the maximum average solution time for the largest instances solved was about two minutes. Moreover, as the number of transportation modes increased, the average solution time also increased due to the additional feasible routes for loads that needed to be enumerated. Only the value of the discount factor α did not seem to affect the average solution time. The search algorithm consistently outperformed the exhaustive enumeration approach showing faster solution times. In small instances, the total transportation costs are relatively small in comparison to the total fixed hub installation costs. As a result, many hub combinations are not evaluated as their fixed hub installation costs were larger than the corresponding upper bound in the search algorithm. Therefore, in small instances, the solution time for the search algorithm was much smaller than the solution time for the exhaustive enumeration approach with up to close to 100% reduction in solution time for some small instances. However, as instances got larger, the share of the total fixed hub installation costs in the total network costs decreased and fewer hub combinations were discarded in the search algorithm. Therefore, the solution time of the search algorithm remained close to the solution time of the exhaustive enumeration approach. In large instances, the search algorithm explored all hub combinations to solve the master problem, but it did not solve all sub-problems for each hub combination. As a result, even in large instances, the search algorithm found the optimal solution sooner than the exhaustive enumeration approach. The minimum amount of reduction in solution time was about 11% for larger instances.

Finally, Table 3.6 shows the average percentage of hub combinations that the search algorithm explored in Set A experiments. As mentioned above, when the number of loads in the network is small and the transportation cost has a small share of the total network costs, only a small portion of hub combinations were explored. However, when the number of loads in the network increased, the search algorithm had to explore most of the hub combinations to find the optimal solution of the master problem.

Table 3.7: Average percentage of hub combinations explored by search algorithm.

# of Nodes	# of Loads	# of Modes = 2						# of Modes = 3					
		Discount factor = 0.5			Discount factor = 0.9			Discount factor = 0.5			Discount factor = 0.9		
		# of Hubs			# of Hubs			# of Hubs			# of Hubs		
		2	**3**	**4**	**2**	**3**	**4**	**2**	**3**	**4**	**2**	**3**	**4**
10	**5 (5%)**	19	10	6	19	11	7	19	10	6	19	10	7
	9 (10%)	25	14	10	26	15	11	25	14	10	26	15	11
	18 (20%)	53	34	24	56	39	29	53	33	23	55	37	28
	45 (50%)	99	89	81	100	93	87	97	89	80	99	91	85
20	**19 (5%)**	62	39	22	64	41	25	62	39	22	64	40	25
	38 (10%)	98	87	69	98	89	73	98	87	68	98	88	71
	76 (20%)	100	100	100	100	100	100	100	100	100	100	100	100
	190 (50%)	100	100	100	100	100	100	100	100	100	100	100	100
30	**44 (5%)**	100	92	68	100	93	72	100	92	68	100	93	71
	87 (10%)	100	100	100	100	100	100	100	100	100	100	100	100
	174 (20%)	100	100	100	100	100	100	100	100	100	100	100	100
	435 (50%)	100	100	100	100	100	100	100	100	100	100	100	100

3.5.2.2 Set B Computational Results

Table 3.7 shows the optimal solution costs for Network Instance 1 for all experimental treatment combinations in Set B. It is observed that in addition to the number of transportation modes and the number of hubs, the number of potential hub locations also had an effect on the optimal solution cost. As the number of potential hub locations increased, the optimal solution cost decreased or stayed at the same level. Table 3.7 also shows the percentage of total network costs that is associated with the fixed costs of hub installation. The percentage of fixed cost in the total network cost increases with the number of hubs, but decreases as the number of nodes and associated flow in the network increase.

Table 3.8. Optimal solution costs for Network Instance 1 (Set B).

# of Nodes	**# of Loads**	**# of Potential Hub Locations**	**Approach**	**Discount factor = 0.5**			
				# of Modes = 2		**# of Modes = 3**	
				V = 2	**V = 4**	**V = 2**	**V = 4**
50	**490 (20%)**	**10% *N***	Total Cost	40,638	47,699	40,543	47,423
			% Fixed Cost	22	37	22	37
		15% *N*	Total Cost	40,440	46,748	40,440	46,678
			% Fixed Cost	21	37	21	37
		20% *N*	Total Cost	40,284	46,535	40,284	46,535
			% Fixed Cost	22	38	22	38
75	**1110 (20%)**	**10% *N***	Total Cost	80,796	84,245	80,796	84,242
			% Fixed Cost	12	22	12	22
		15% *N*	Total Cost	80,796	83,862	80,766	83,618
			% Fixed Cost	12	22	11	22
		20% *N*	Total Cost	80,796	83,862	80,766	83,618
			% Fixed Cost	12	22	11	22
100	**1980 (20%)**	**10% *N***	Total Cost	134,198	135,568	133,665	134,743
			% Fixed Cost	6	13	6	13
		15% *N*	Total Cost	134,198	134,768	133,665	134,266
			% Fixed Cost	6	13	6	13
		20% *N*	Total Cost	134,198	133,988	133,287	132,584
			% Fixed Cost	6	13	6	13
150	**4470 (20%)**	**10% *N***	Total Cost	289,540	274,918	287,821	272,209
			% Fixed Cost	3	7	3	7
		15% *N*	Total Cost	289,540	274,918	287,821	272,209
			% Fixed Cost	3	7	3	7
		20% *N*	Total Cost	288,453	273,222	287,405	270,263
			% Fixed Cost	3	7	3	7

Table 3.8 shows the average solution times over five instances of each experimental treatment combination in Set B. In addition to the network size, number of open hubs, and number of existing transportation modes, the average solution time was also affected by the size of the set of potential hub locations, *P*. The fastest average solution time was less than one second, while the longest average solution time corresponding to the largest problem instances solved was less than 25 minutes. Similar to Set A, the search algorithm consistently outperformed the exhaustive enumeration approach showing faster solution times. However, as the percentage of fixed costs in total network cost was relatively small in Set B instances, the search algorithm could not discard any feasible hub combinations and the efficiency of the search algorithm resulted from discarding some of the sub-problems. As a result, the average reduction in solution times was relatively small in larger Set B instances.

A summary of all the trends observed in the results for both Set A and Set B instances are presented in Figure 3.6.

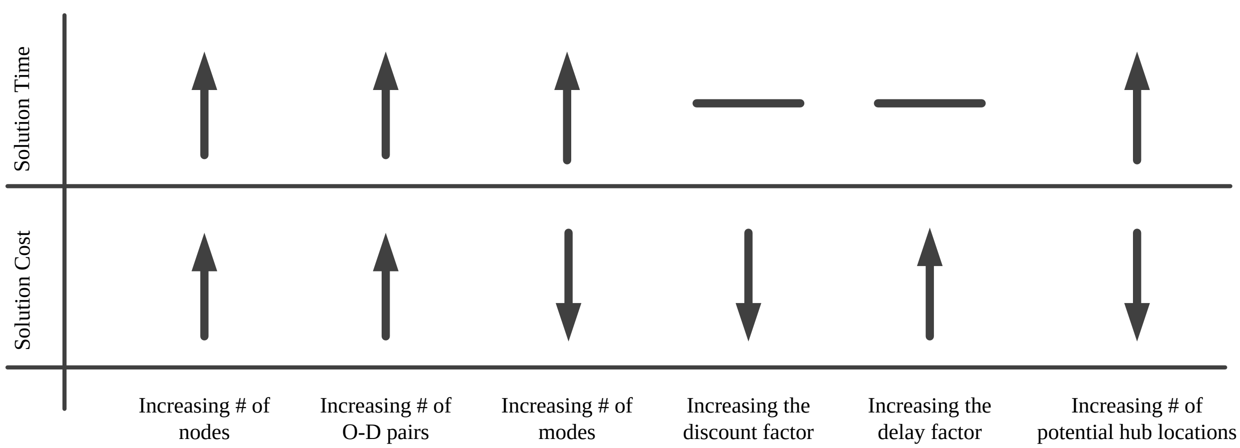


Figure 3.6. Summary of observed trends in the results for both sets of instances.

Table 3.9. Set B average solution times (in seconds).

# of Nodes	# of Loads	# of Potential Hub Locations	Approach	Discount factor = 0.5			
				# of Modes = 2		# of Modes = 3	
				V = 2	V = 4	V = 2	V = 4
50	**490 (20%)**	**10% *N***	**Enum.**	0.027	0.049	0.034	0.047
			SA	0.025	0.047	0.031	0.044
			%Diff.	-8	-5	-8	-8
		15% *N*	**Enum.**	0.115	0.391	0.122	0.422
			SA	0.112	0.362	0.115	0.402
			%Diff.	-3	-7	-5	-5
		20% *N*	**Enum.**	0.187	1.122	0.190	1.246
			SA	0.184	1.080	0.187	1.204
			%Diff.	-2	-4	-2	-3
75	**1110 (20%)**	**10% *N***	**Enum.**	0.264	0.829	0.280	0.984
			SA	0.253	0.802	0.265	0.899
			%Diff.	-4	-3	-5	-9
		15% *N*	**Enum.**	0.527	3.934	0.566	4.397
			SA	0.496	3.819	0.534	4.221
			%Diff.	-6	-3	-6	-4
		20% *N*	**Enum.**	0.982	15.978	1.049	17.925
			SA	0.942	15.522	0.980	17.422
			%Diff.	-4	-3	-7	-3
100	**1980 (20%)**	**10% *N***	**Enum.**	0.740	4.487	0.801	4.984
			SA	0.718	4.331	0.764	4.774
			%Diff.	-3	-3	-5	-4
		15% *N*	**Enum.**	1.718	27.894	1.847	31.224
			SA	1.682	27.678	1.760	30.561
			%Diff.	-2	-1	-5	-2
		20% *N*	**Enum.**	3.064	99.921	3.211	108.683
			SA	3.014	97.526	3.120	108.081
			%Diff.	-2	-2	-3	-1
150	**4470 (20%)**	**10% *N***	**Enum.**	3.895	66.251	4.226	76.255
			SA	3.747	61.424	3.912	69.642
			%Diff.	-4	-7	-7	-9
		15% *N*	**Enum.**	9.750	416.365	9.985	483.021
			SA	8.955	400.102	9.429	456.044
			%Diff.	-8	-4	-6	-6
		20% *N*	**Enum.**	16.398	1,319.213	17.973	1,495.364
			SA	15.485	1,248.298	16.315	1,402.901
			%Diff.	-6	-5	-9	-6

3.6 Conclusions and Future Work

Strategically designing intermodal logistics networks to optimize some specific criteria becomes even more relevant given the expected growth of intermodal transportation demand. While integrating relevant tactical and operational decisions such as transportation mode and load route selection improves the applicability of logistics networks designed using mathematical programming approaches, it also adds more complexity to the modeling of this problem and affects its tractability. To overcome this challenge, a composite variable formulation was developed and solved to optimality by implementing a decomposition algorithm. According to the results obtained in our computational experiments, the optimal solution costs depends on the network size (i.e., number of nodes and loads, and the number of transportation modes), number of hubs to be opened, and the value of the discount factor that is applied to the inter-hub transportation cost.

Also, computational times required to obtain an optimal solution increased with the size of the instance being solved. According to computational experiment results, the proposed solution approach was able to find optimal logistics network designs for networks that consist of 150 nodes and about 4,500 loads in less than 20 seconds when locating two hubs. While it required about 25 minutes when locating four hubs. Long computational times could be reduced with a parallel computing implementation of the proposed solution method. Alternatively, a more efficient solution approach such as column generation could be applied to solve the master problem for larger-size problem instances. Both of these two approaches are potential future research directions.

Also, similar to most previous research studies, a constant discount factor was considered to model the effect of economies of scale on the transportation cost. In order to improve the applicability of this model to design networks that can be implemented in practice with minimal reconfiguration, a more realistic cost function could be considered in the future. Similarly, some other tactical and operational decisions such as resource levels at terminals or equipment allocation could be integrated into the model to improve the applicability of the designed intermodal logistics networks. The research challenge is that realistic assumptions and more decisions should be integrated in the model in a way such that the tractability of mathematical model would not be affected significantly.

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4 Bender's Decomposition Algorithm for Integrated Intermodal Logistics Network Design[3]

4.1 Abstract

The integrated intermodal logistics network design problem is a planning problem that integrates the strategic decision of determining intermodal terminal locations with the tactical decisions of selecting regular routes and modes of transportation for loads in a freight transportation system. This problem has been previously formulated using a composite variable formulation and solutions have been found using a decomposition-based search algorithm. In this study, a Bender's decomposition algorithm is implemented to obtain optimal solutions for this problem. To improve the performance of the implemented Bender's decomposition algorithm, a preprocessing heuristic is developed that reduces the size of instances and generates better upper bounds for the problem. Computational results show that the developed solution approach is able to obtain exact solutions for large instances of up to 250 nodes and 12,450 loads in reasonable computational times. The effects of design parameters on solution characteristics are also analyzed using the results of the computational experiments and a few general insights are provided.

Keywords: intermodal transportation; logistics; network design; Bender's decomposition; optimization

4.2 Introduction

Intermodal transportation uses at least two different transportation modes (e.g., truck, rail, ship, air) to move freight loads that are in the same transportation unit (e.g., a shipping container) from origin to destination (Macharis and Bontekoning, 2004). In general, intermodal transportation service is provided by several carriers that handle load transfers at intermodal terminals. For example, a freight load can be moved by truck from a shipper's facility to either a shipping port directly or to a rail yard first where it will be consolidated with other loads on a train that will

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then move them to a shipping port. At the shipping port, freight loads that are still in the same container will be transferred to a freight ship to be moved to a different port that might be on a different continent. Finally, these freight loads will be delivered to their destinations using trucks or other transportation mode as part of another intermodal network (Crainic and Kim, 2007). Planning an intermodal transportation network that requires cooperation of several stakeholders (i.e., carriers, operators, terminals, policy makers, etc.) is not an easy task. However, due to the benefits of intermodal transportation associated with less environmental and social costs when compared to long-haul trucking (i.e., less road congestion, environmental pollution, infrastructure damage, road accidents, etc.) (Arnold et al., 2004), policy makers have started to promote the use of intermodal freight transportation as a valid alternative for freight transportation. For example, the European Commission attempted to shift a significant portion of freight demand from road to other sustainable transportation modes in Europe thorough the Marco Polo program ("Transport - Marco Polo - European Commission," 2014)

The increasing shift to intermodal transportation and the growth of freight transportation demand have resulted in a higher demand for intermodal freight transportation that has been projected to grow even faster in the next few decades. According to the Freight Analysis Framework 4 (FAF4, 2016) , the demand for intermodal freight transportation in the U.S. will increase approximately 80% from 2016 to 2045. Satisfying this emerging demand will require enhancing the capacity of current intermodal facilities or even the construction of new intermodal facilities. The strategic location of these new intermodal facilities not also affects the performance of the intermodal transportation logistics network (i.e., in terms of both transportation cost and service time), but is also very critical for the performance of every single mode logistics network that is part of the intermodal transportation network.

As intermodal logistics networks become more relevant, more researchers have addressed the Intermodal Logistics Network Design (ILND) problem. The ILND problem is a strategic planning problem that determines the number and location of intermodal terminals as well as the allocation of customers to terminals. Several mathematical formulations and solution approaches have been developed to address this problem (as discussed later in Section 4.3). However, despite their valuable insights, most of these approaches have been metaheuristic approaches that are not able to guarantee solution optimality. At the same time, the few studies that have attempted to find optimal solutions for the ILND problem consider very restrictive assumptions that limit their applicability and are not able to handle real size instances of the ILND problem. Therefore, there is still a need for developing solution approaches to find exact solutions for real size instances of the ILND problem in reasonable computational times.

This study is an extension of the work presented in Chapter 3. Here, a Bender's decomposition approach is implemented to solve the composite variable formulation that was previously developed in Chapter 3. Moreover, a pre-processing heuristic was developed in this study that reduces the size of problem and is used to accelerate the Bender's decomposition method. Using this new solution approach, we are able to solve large instances of the ILND problem (with 250 cities and about 12,500 origin-destination pairs) in reasonable computational times. The Bender's decomposition approach was implemented in this research because of its high performance in similar problems. A brief discussion about the application of Bender's decomposition to similar problems in the literature can be found in Section 4.3.

Similar to Chapter 3, this research is intended to help decision makers of network operators for large logistics companies providing intermodal freight transportation service including Class I railroads and large full truckload carriers. Network operators are responsible for making the strategic decisions of determining and designing the intermodal logistics network topology (Macharis and Bontekoning, 2004).

The rest of this chapter is organized as follows. A review of previous studies in intermodal logistics network design and a review of the use of Bender's decomposition in similar problems are presented in Section 4.3. In Section 4.4, we define the problem under study, re-introduce the mathematical formulation presented in Chapter 3, and describe the solution approach developed in this research. Computational test results are presented in Section 4.5. Finally, concluding remarks and future research directions are presented in Section 4.6.

4.3 Literature Review

As intermodal transportation demand continues to increase, the body of research in this field also continues to increase significantly (SteadieSeifi et al. (2014)). An important strategic planning problem studied in this field is the design of the intermodal transportation network which includes locating intermodal facilities. To address this problem, many researchers have assumed that the intermodal transportation network is similar to a hub-and-spoke network and used different approaches to find the best location of terminals and the allocation of costumers to these terminals. However in practice, intermodal transportation networks have characteristics that make them different from conventional hub-and-spoke networks. For example, many hub-and-spoke networks prevent direct transportation between spokes while it is common in intermodal transportation networks that some of the freight loads be transported directly from origin to destination without visiting any intermodal terminal. The reader can find comprehensive reviews of research studies addressing the design of hub-based networks for different applications in Alumur and Kara (2008), Campbell and O'Kelly (2012) and Farahani et al. (2013). Similarly, Macharis and Bontekoning (2004), Caris et al. (2013) and SteadieSeifi et al. (2014) provide comprehensive reviews of research studies in intermodal transportation planning.

Intermodal transportation logistics networks have been traditionally modeled using mathematical programming. Arnold et al. (2001), Arnold et al. (2004) and Racunica and Wynter (2005) were early attempts of using mathematical programming formulations to solve the ILND problem. Later, Smilowitz and Daganzo (2007) used mathematical programming and developed a solution approach for designing an intermodal transportation network for express package delivery. Rahimi et al. (2008) used a location-allocation formulation to find the optimal number and location of inland intermodal ports in an application in California to minimize total facility and transportation costs. Limbourg and Jourquin (2009) modeled the intermodal logistics network as a p-hub median problem. The authors assumed that each customer can be allocated to only one hub, and then they proposed an iterative procedure to find the optimal location of intermodal hubs among several potential locations.

Ishfaq and Sox (2011) and Ishfaq and Sox (2012) modeled the ILND problem as a multiple-allocation *p*-hub median problem. Both assumed that each freight load has a service time requirement and can visit up to two intermodal terminals in its route from origin to destination. Tabu Search was used in both to find near optimal solutions. Ishfaq and Sox (2012), in particular, incorporated limitations on resource levels at terminals by modeling terminal operations as a G/G/1 queuing system. This allowed them to estimate delay times at terminals more accurately in comparison to using a constant delay factor. In both studies, the objective was to minimize the total network costs including the fixed cost of opening hubs, the cost of adapting them to different transportation modes, and transportation and service costs.

In another study, Alumur et al. (2012) modeled the intermodal logistics network as a single allocation hub network design problem. They developed a Lagrangian decomposition-based heuristic with valid inequalities and variable reduction to obtain near optimal solutions for a case of a network with 81 nodes and 16 potential hub locations. About at the same time, Sörensen et al. (2012) and Sörensen and Vanovermeire (2013) focused on developing efficient solution approaches for the mathematical formulation developed by Arnold et al. (2001) and a bi-objective version of this formulation, respectively. In the mathematical formulation presented in Arnold et al. (2001) freight loads can be sent point-to-point as well as visit at most two intermodal terminals throughout their route from origin to destination. Sörensen et al. (2012) were able to find near optimal solutions for instance problems with 100 nodes using a two-stage approach, while Sörensen and Vanovermeire (2013) applied a greedy randomized adaptive search (GRASP) procedure to estimate optimal Pareto sets.

More recently, environmental and sustainability aspects have also been incorporated in addition to economic objectives (i.e., minimization of transportation and terminal installation costs) in the design of intermodal logistics networks. Single and multi-objective mathematical formulations have been developed to account for costs associated with emissions in intermodal transportation networks. For example, Zhang et al. (2013) proposed a mathematical formulation that minimizes the cost of CO_2 emissions associated with each shipment in an intermodal network. Near optimal solutions were obtained for a real application in the Netherlands by implementing a genetic algorithm. In another study, Assadipour et al. (2015) developed a non-linear mixed integer program (MIP) for a rail-truck intermodal transportation network of hazardous materials. Qu et al. (2016) developed a nonlinear integer mathematical formulation to find optimal hub locations for a real case study in the United Kingdom with eleven locations. The authors linearized the proposed mathematical formulation that considered greenhouse gas emission costs and showed how the proposed model can be modified into a bi-objective formulation. Baykasoğlu and Subulan (2016) developed an MIP model for a multi-objective intermodal transportation load planning problem. The authors proposed a few multiple objective optimization approaches to handle conflicting objectives simultaneously under crisp and fuzzy decision making environments. The authors then tested their solution approach with a real-life case study in Turkey.

Although the research studies presented above have all been able to find valuable insights, they have not been able to find optimal solutions for non-trivial instances of the integrated ILND problem. To the best of our knowledge, Chapter 3 is the first attempt to solve the integrated ILND problem exactly. The authors developed a composite variable formulation that models the consolidation effects on transportation cost and time using constant discount and delay factors, respectively. The authors developed a decomposition-based search algorithm that is able to obtain optimal solutions for problem instances of up to 150 nodes and 4,500 loads in reasonable computational times. However, there is a need for developing more efficient solution approaches that can solve larger instances of the integrated ILND problem to be more applicable in real world instances. The current study tries to close this gap by proposing an accelerated Bender's decomposition approach that is able to solve large instances (up to 250 nodes and 12,450 loads) of the composite variable formulation proposed in Chapter 3.

Bender's decomposition has been selected because of its proven performance in similar problems. For example, Binato et al. (2001) implemented a Bender's decomposition approach to find an optimal power transmission network design for a case in Brazil. Üster et al. (2007) implemented a Bender's decomposition algorithm to solve the multi-product closed-loop supply chain network design problem. The authors developed an efficient dual solution approach that enables them to add strong Bender's cuts in addition to the classical single Bender's cut approach. They concluded that the quality of the Bender's cut has a significant effect on the performance of the Bender's decomposition approach. In another study, Kewcharoenwong and Üster (2014) implemented Bender's decomposition to solve a fixed-charge relay network design problem applied to long-distance translucent optical telecommunication networks. The authors developed several accelerating techniques including strengthened and disaggregated Bender's cuts and an upper bound heuristic to both obtain and tighten optimality Bender's cuts and improve the performance of the Bender's decomposition algorithm. More recently, Makui and Ghavamifar (2016) implemented Bender's decomposition to solve a supply chain network design problem under risk, disruption and uncertainty.

4.4 Methodology

4.4.1 Problem Definition

The location of intermodal terminals significantly affects and is affected by the routing of freight loads. Therefore, in order to optimize the performance of an intermodal logistics network, the intermodal terminal location problem should be integrated with the problem of finding regular routes and transportation modes for the freight loads. The objective of the integrated LND problem is to find the optimal intermodal network design that minimizes the total network costs including the fixed cost of opening intermodal terminals and the transportation cost of the freight loads. Several assumptions were considered to formulate this problem.

First, an intermodal logistics network is assumed to be formed by N nodes representing origins or destinations of freight loads as well as existing and additional candidate locations for intermodal terminals. A known subset P of these N nodes forms the set of potential terminal locations from which V locations need to be selected as intermodal terminals. Note that there is a fixed cost associated with opening an intermodal terminal which differs depending on the location of a node. The level of geographical aggregation for nodes could be modified to model regional, national, and even international intermodal logistics networks. Consequently, the selected level of geographical aggregation will determine the size of the instance.

We also assumed that there are *L* different freight loads (i.e., shipments formed by containers) that should be served. Each freight load has an origin node, a destination node, number of containers, and a maximum allowed transportation time. Containers in a freight load cannot be split in their movement from origin to destination, and thus an “all-or-nothing” policy applies when route and transportation mode decisions are made for a particular freight load. The network topology is assumed to be hybrid combining the point-to-point, connected hubs, and static routes topologies described by Woxenius (2007). Therefore, freight loads can be shipped directly from their origin to their destination or they can be relayed at one or more intermodal terminals. Consequently, our network design problem is different than the traditional hub-and-spoke network design problem.

Regardless of the number of transfers (if any) in route, the total transportation time for each freight load has to satisfy the specified maximum allowed transportation time for the load. At intermodal terminals, different freight loads are consolidated (if appropriate) and then transferred to a different transportation mode. The freight loads are then sent to another intermodal terminal or directly to their destinations. The consolidation of freight loads reduces the unit transportation cost per container for movements between intermodal terminals due to economies of scale (i.e., by sharing equipment and reducing the number of trips). However, the consolidation of freight loads also increases their transportation time since the consolidation process itself requires time at the terminals which is usually affected by the freight loads experiencing delays due to the high utilization of the handling equipment at the terminal. Similar to most research studies in this field, constant discount and delay factors are used to account for the consolidation effects on transportation unit cost per load and transportation time, respectively (Ishfaq and Sox, 2012, 2011; Limbourg and Jourquin, 2009). The two constant factors can be estimated from past data or using expert opinion.

4.4.2 Mathematical Formulation

In this study we used the same composite variable formulation developed in Chapter 3. A composite variable formulation allows us to implicitly capture difficult constraints in the variable definition and avoid explicitly including them as complicating constraints in the mathematical formulation. In this research, a complete feasible route from origin to destination is considered as a single composite variable. Before formulating the mathematical model, all routes that can be used to send load *l* from its origin to its destination are generated. The transportation cost and total transportation time for each route are calculated using the constant discount and delay factors. Then, the total transportation time for each route is checked against the maximum allowed transportation time for that load. In this way, all infeasible routes are excluded from the mathematical formulation, and the transportation time constraint does not need to be included in the mathematical formulation. The reader is referred to Chapter 3 for more details and examples on how the composite variables are generated for the formulation presented below.

3.2.1 Notation

<u>Sets and Parameters</u>

N	set of nodes *n*,
P	set of potential terminal locations, $P \subset N$,
M	set of transportation modes *m*,
L	set of loads *l*,
V	number of terminals in a feasible terminal combination,
H	set of terminal combinations *h*, each terminal combination consists of *V* nodes corresponding to terminal locations,
$R_{l,h}$	set of composite variables (i.e. feasible routes) *i* to transport load *l* when terminals in terminal combination *h* are open,
TW_l	maximum allowed transportation time for load *l*,
F_h	fixed cost of opening terminals for terminal combination *h*,
d_l	demand quantity (in number of containers) for load *l*,
$C_{l,i}^{h}$	per load transportation cost of moving load *l* on route *i* when terminals in terminal combination *h* are open,
$t_{l,i}^{h}$	time to transport load *l* on route *i* when terminals in terminal combination *h* are open,

<u>Decision Variables</u>

$$r_{l,i}^{h} = \begin{cases} 1 & \text{if feasible route } i \text{ is selected to transport load } l \text{ using terminal combination } h \\ 0 & \text{otherwise,} \end{cases}$$

$$Y_h = \begin{cases} 1 & \text{if terminals in terminal combination } h \text{ are open} \\ 0 & \text{otherwise.} \end{cases}$$

3.2.2 Mathematical Formulation

The mathematical programming formulation for the integrated ILND problem follows:

$$Minimize \sum_{h}^{H} F_h Y_h + \sum_{h}^{H} \sum_{l}^{L} \sum_{i}^{R_{l,h}} C_{l,i}^{h} . d_l . r_{l,i}^{h} \tag{4.1}$$

Subject to:

$$\sum_{l}^{L} \sum_{i}^{R_{l,h}} r_{l,i}^{h} \leq |L| Y_h \qquad \forall h \in H \tag{4.2}$$

$$\sum_{h}^{H} \sum_{i}^{R_{l,h}} r_{l,i}^{h} = 1 \qquad \forall l \in L \tag{4.3}$$

$$\sum_{h}^{H} Y_h = 1 \tag{4.4}$$

$$Y_h = \{0,1\} \qquad \forall h \in H \tag{4.5}$$

$$r_{l,i}^{h} = \{0,1\} \qquad \forall l \in L, \forall i \in R_{l,h}, \forall h \in H \tag{4.6}$$

In the above mathematical formulation, the objective function (4.1) minimizes the total logistics network costs. Total logistics network costs consist of the fixed cost of opening intermodal terminals and the transportation costs, but neglect operation costs related to handling of freight at terminals. Constraint (4.2) enforces that terminals cannot be used if they are not open. Note that no capacity restrictions were considered for open terminals. Constraint (4.3) enforces that all demand should be satisfied by selecting exactly one composite for a particular load. Constraint (4.4) ensures that only one terminal combination be selected. And finally, Constraints (4.5) and (4.6) are the variable type constraints.

4.4.3 Bender's Decomposition Solution Approach

There are two sets of decision variables in the mathematical formulation presented in Section 4.4.2, one that indicates the intermodal terminal locations (i.e., by selecting a single terminal combination), and one that indicates the routes for freight loads (i.e., by selecting a composite variable for each freight load). However, the two sets of variables appear together only in Constraint (4.2). As such, if the variables related to the intermodal terminal locations are temporarily fixed the remaining mathematical formulation becomes considerably more tractable. This structure of the formulation makes it convenient to use the Bender's decomposition approach for solving larger size instances of the integrated ILND problem (Geoffrion, 1972). Bender's decomposition allows solving a smaller size master problem and associated sub-problems instead of solving the original mathematical formulation. The master problem is usually a mixed integer program (MIP) with an auxiliary continuous variable that facilitates the connection between the master problem and the sub-problems through Bender's cuts. A sub-problem is constructed by entering the values (i.e., selected terminal combination) obtained by solving the master problem. Once the dual of the sub-problem has been solved, Bender's cuts are generated and added to the master problem. These Bender's cuts could be optimality cuts if the sub-problem is feasible or feasibility cuts if the sub-problem is not feasible. In the integrated ILND problem, the optimal routes for each freight load can be obtained independently of other routes. Therefore, the sub-problem can be further decomposed into L small sub-problems, each corresponding to one of the freight loads. This will result in a more efficient solution approach because at each iteration, smaller sub-problems need to be solved.

In summary, in the Bender's decomposition approach, the master problem is solved and its solution (i.e., the integer variables $\boldsymbol{Y}$) is used to construct L sub-problems where each sub-problem corresponds to one freight load. Solving each of these sub-problems then creates one

Bender's cut. These cuts are then added to the master problem to complete one iteration of the Bender's decomposition algorithm. Therefore, the master problem and the sub-problem are solved iteratively until the optimal solution has been found or a desirable optimality gap is achieved. Note that while this approach provides a good framework for solving the integrated ILND problem, we improved its performance by developing a heuristic approach that reduces the size of instances and provides a better upper bound for the Bender's decomposition approach. The developed heuristic is presented in Section 4.4.3.4.

4.4.3.1 Sub-problem

Once a terminal combination (i.e., set of intermodal terminal locations) is given ($\boldsymbol{Y}$), the mathematical formulation for the integrated ILND problem reduces to the following sub-problem $SP(\boldsymbol{r}|\widehat{\boldsymbol{Y}})$ with only $\boldsymbol{r}$ variables:

Integrated ILND Sub-Problem ($SP(\boldsymbol{r}|\widehat{\boldsymbol{Y}})$):

$$Minimize \sum_{l}^{L}\sum_{i}^{R_{l,\hat{h}}} C_{l,i}^{\hat{h}}.d_l.r_{l,i}^{\hat{h}} \tag{4.7}$$

Subject to:

$$\sum_{l}^{L}\sum_{i}^{R_{l,\hat{h}}} r_{l,i}^{\hat{h}} \leq |L|\hat{Y}_h \tag{4.8}$$

$$\sum_{i}^{R_{l,\hat{h}}} r_{l,i}^{\hat{h}} = 1 \qquad \forall l \in L \tag{4.9}$$

$$r_{l,i}^{\hat{h}} = \{0,1\} \qquad \forall l \in L, \forall i \in R_{l,\hat{h}} \tag{4.10}$$

The sub-problem $SP(\boldsymbol{r}|\widehat{\boldsymbol{Y}})$ is basically the route and transportation mode selection problem for all freight loads taking into account that the terminals are opened at the nodes indicated by $\widehat{Y_h}$. However, the optimal route for each freight load can be found separately from other freight loads. As a result, the sub-problem $SP(\boldsymbol{r}|\widehat{\boldsymbol{Y}})$ is decomposable and can be separated into L sub-problems $SP_l(\boldsymbol{r_l}|\widehat{\boldsymbol{Y}})$, one for each freight load as follows.

Integrated ILND Sub-Problem for Freight Load *l* ($SP_l(\boldsymbol{r}|\widehat{\boldsymbol{Y}})$):

$$Minimize \sum_{i}^{R_{l,\hat{h}}} C_{l,i}^{\hat{h}}.\, d_l.\, r_{l,i}^{\hat{h}} \tag{4.11}$$

Subject to:

$$\sum_{i}^{R_{l,\hat{h}}} r_{l,i}^{\hat{h}} = 1 \tag{4.12}$$

$$r_{l,i}^{\hat{h}} = \{0,1\} \qquad \forall i \in R_{l,\hat{h}} \tag{4.13}$$

To generate the Bender's cuts, the dual of sub-problems $SP_l(\boldsymbol{r_l}|\widehat{\boldsymbol{Y}})$ need to be formulated and solved. Then, the dual sub-problem $SP_l\left(\boldsymbol{r_l}\middle|\widehat{\boldsymbol{Y}}\right)$ can be formulated using the dual variables $\alpha_l^{\hat{h}}$ as follows:

Integrated ILND Dual Sub-Problem for Freight Load *l* ($DSP_l(\boldsymbol{\alpha_l}|\widehat{\boldsymbol{Y}})$):

$$Maximize \ \alpha_l^{\hat{h}} \tag{4.14}$$

Subject to:

$$\alpha_l^{\hat{h}} \leq C_{l,i}^{\hat{h}}\, d_l \qquad \forall i \in R_{l,\hat{h}} \tag{4.15}$$

$$\alpha_l^{\hat{h}} = unristricted\ in\ sign \tag{4.16}$$

4.4.3.2 Bender's Cuts

Bender's cuts generated with the sub-problems are added to the master problem. A continuous variable B_l, and the values obtained by solving the dual sub-problem ($DSP_l(\boldsymbol{\alpha_l}|\widehat{\boldsymbol{Y}})$ are used to generate a single Bender's cut as follows:

$$B_l \geq \alpha_l^{\hat{h}}\, Y_h \tag{4.17}$$

Note that we were able to generate a Bender's cut for each freight load because the original sub-problem was decomposed into L different sub-problems, each for one freight load. To generate a valid Bender's cut associated with freight load l, the sub-problem $SP_l(\boldsymbol{r_l}|\widehat{\boldsymbol{Y}})$ is required to be feasible which means that we need to have at least one route from the origin of freight load l to its destination that satisfies the maximum allowed transportation time for freight load l. Otherwise, we cannot ship freight load l and the sub-problem $SP_l(\boldsymbol{r_l}|\widehat{\boldsymbol{Y}})$ becomes infeasible. In such case, we have to generate a feasibility cut in the following form:

$$0 \geq \alpha_l^{\hat{h}}\, Y_h \tag{4.18}$$

The feasibility cuts will result in poor lower bounds (Kewcharoenwong and Üster, 2013). So, one other advantage of separating the sub-problem and generating one Bender's cut for each of the freight loads is that we can add optimality cuts or feasibility cuts based on the feasibility of the corresponding sub-problem. While, if we have only one sub-problem for all of the freight loads, we would have to generate a feasibility cut even if only one of the freight loads couldn't be shipped (i.e., has an infeasible sub-problem). This would reduce the performance of the solution approach.

4.4.3.3 Master Problem

The master problem is a mixed integer program (MIP) which deals with finding the optimal terminal combination (i.e., intermodal terminal locations) as follows:

Integrated ILND Master Problem ($MP(\boldsymbol{Y}|\widehat{\boldsymbol{\alpha}})$):

$$Minimize \sum_{h}^{H} F_h Y_h + \sum_{l}^{L} B_l \tag{4.19}$$

Subject to:

$$\sum_{h}^{H} Y_h = 1 \tag{4.20}$$

(set of Bender's cuts) (4.21)

$$Y_h = \{0,1\} \qquad \forall h \in H \tag{4.22}$$

$$B_l \geq 0 \qquad \forall l \in L \tag{4.23}$$

The continuous variables B_l were added to the master problem to enable the addition of the Bender's cuts generated from the sub-problems into the master problem. Moreover, at each iteration of the Bender's decomposition algorithm, L new Bender's cuts are added to the previous set of Bender's cut. The pseudo code of the Bender's decomposition approach is presented in Figure 4.1.

```
Initialize UB = ∞, α̂ = 0 set of Bender's cuts = ∅
Solve MP(Y|α̂) to obtain Z_MP and Y
Set LB = Z_MP
While (UB ≠ LB) {
   For each freight load l {
         Solve DSP_l(α_l|Ŷ) to obtain Z_DSP_l and α_l^ĥ
   }
   If (Z_MP − Σ_l B_l + Σ_l Z_DSP_l < UB) {
      UB = Z_MP − Σ_l B_l + Σ_l Z_DSP_l
      Ȳ = Ŷ
   }
   If (UB = LB) {
      Break
   }
   Generate Bender's cuts (either optimality cut or feasibility cut) and add them to MP(Y|α̂)
   Solve MP(Y|α̂) to obtain Z_MP, Y and B_l
   Set LB = Z_MP
}
Solve SP(r|Ȳ) to obtain r̄
      Return Ȳ and r̄
```

Figure 4.1: The pseudo-code of Bender's decomposition approach

In preliminary testing, the Bender's decomposition approach proved to have a good performance, however we can increase its performance by applying a preprocessing heuristic algorithm which reduces the size of problem instances and enhances the quality of the upper bound.

4.4.3.4 Preprocessing Heuristic

A preprocessing heuristic was developed to improve the performance of the Bender's decomposition algorithm by reducing the size of the problem instance and generating a better upper bound for the problem. This heuristic initially assumes that an intermodal terminal is opened at all potential terminal locations. Then, based on this assumption, the optimal route for each freight load can be obtained by solving the sub-problem $SP_l(r_l|Y_h = 1\ \forall h\ \in H)$ for each freight load. If at least one freight load is found to be infeasible even with intermodal terminals open at all potential locations, we can conclude that this instance of the problem is infeasible without any further exploration. Otherwise, we can use the optimal routes for freight loads to reduce the instance size by considering the following two situations. First, if the optimal route for a freight load is point-to-point when all potential intermodal terminals are open, then the optimal route for this load in the optimal network design (when only terminals at the optimal locations are open) would be point-to-point as well. Therefore, we can eliminate this freight load from the set of all loads which reduces the number of freight loads in the problem. Second, we can enumerate the number of times each potential terminal location is used in the optimal routes for freight loads when all terminals are open. We can then eliminate the potential locations that are never used or used only a few times from the set of potential intermodal terminal locations. Appendix B shows the proof that the preprocessing heuristic doesn't eliminate the optimal solution.

In addition, we also can improve the initial upper bound of the Bender's decomposition approach by using the total network cost obtained when only the first V potential terminal locations that are used the most are open. Our computational experimentation shows that this preprocessing heuristic significantly increased the performance of the Bender's decomposition algorithm. The pseudo code of this heuristic approach is presented in Figure 4.2.

```
Set U_p = 0, ∀ p ∈ P
For all freight load l {
   Solve SP_l(r_l | Y_h = 1 ∀h ∈ H)
   If (r_l is point-to-point) {
      Discard freight load l
   }
   If (r_l pass through potential terminal location p) {
      U_p += 1
   }
}
For all potential terminal location p {
   If (U_p = 0) {
      Discard potential terminal location p
   }
}
```

Figure 4.2: The pseudo-code of preprocessing heuristic

The preprocessing heuristic is applied prior to the Bender's decomposition algorithm. The whole procedure is called *accelerated Bender's decomposition*. Preliminary computational experiments showed that the accelerated Bender's decomposition algorithm can solve large instances of up to 250 nodes and 12,450 freight loads in reasonable times. A detailed discussion on computational experiments is presented in Section 4.5.

4.5 Computational Experiments

4.5.1 Experimental Design

We evaluated the performance of the proposed solution approach using two sets of experiments similar to the approach used in Chapter 3. The first set of experiments (Set A) represents small instances with 10, 20 and 30 nodes where all nodes can be considered as a potential intermodal terminal location, while the second set of experiments (Set B) represents medium to large instances with 50, 75, 100, 150, 200 and 250 nodes in which only a subset of nodes are considered to be the set of potential intermodal terminal locations. For both sets of experiments, nodes coordinates were generated randomly in a 1×0.5 rectangular area. We used the configuration of the solutions obtained and the computational time to obtain optimal solutions as the performance metrics of interest in this study.

Regarding freight loads, L different freight loads were selected randomly from all possible O-D pairs in the complete network. Similar to Chapter 3, for each freight load, the maximum allowed transportation time and number of containers were selected randomly between 2 and 6 time units and 50 and 150 containers respectively. It was assumed that each freight load can visit up to two terminals through its entire route and that all drayage operations can be handled only by trucks. Note that while the last two assumptions are not imposed by the proposed solution approach, they are common limitations in most real world instances and are considered in many of the previous studies including Chapter 3 and Ishfaq and Sox (2011) . For each value of L, five different sets of loads were generated. The value of L for each of the experiments sets is shown in Table 4.1.

All network costs were also generated similar to Chapter 3. Fixed costs associated with opening intermodal terminals are generated randomly between 4,000 and 5,500. Moreover, the per load transportation cost as well as the travel time between nodes *i* and *j* depend on the distance between the two nodes and vary based on the transportation mode. Note that while the distance between origin and destination has a significant role in transportation cost and time, in real world instances they are not exactly proportional to the distance (i.e., due to congestion, service regulations, etc.). Therefore, random values between 0 and 1 were added to the transportation time and cost to violate the triangular inequality in the experiments. Equations (4.24) to (4.29) show the formulas used to calculate transportation cost and time for each node pair. In these equations, *Random* (0, 1) is a uniformly distributed random variable between 0 and 1. It was also assumed that a higher numbered transportation mode represents a mode that provides less expensive service over long distance, while it is more time consuming.

Mode (m)	**Transportation cost per load between nodes *i* and *j* using mode *m* (C_{ij}^{m})**	
1	$C_{ij}^{1} = Distance\ (i,j)\ /\ 2\ +\ Random(0,1)$	(4.24)
2	$C_{ij}^{2} = Distance\ (i,j)\ /\ 3\ +\ Random(0,1)$	(4.25)
3	$C_{ij}^{3} = Distance\ (i,j)\ /\ 4\ +\ Random(0,1)$	(4.26)
Mode (m)	**Time to move a load between nodes *i* and *j* using mode *m* (t_{ij}^{m})**	
1	$t_{ij}^{1} = Distance\ (i,j)\ +\ Random(0,1)$	(4.27)
2	$t_{ij}^{2} = Distance\ (i,j) \times 1.5\ +\ Random(0,1)$	(4.28)
3	$t_{ij}^{3} = Distance\ (i,j) \times 2\ +\ Random(0,1)$	(4.29)

Finally, different values for discount factor (α), number of modes (*T*), number of terminals (*V*), and number of potential terminal locations were considered in solving all instances. The values used for the discount factor (α) and the delay factor (β) were set equal to values previously used in Chapter 3 and Ishfaq and Sox (2011). The list of all parameters and their values used in our computational experiments are shown in Table 4.1.

Table 4.1: Computational experiment parameters and their values.

Parameter	Set A	Set B
Number of Nodes (*N*)	10, 20, 30	50, 75, 100, 150, 200, 250
Number of Loads (*L*)	5%, 10%, 20% and 50% of all possible O-D pairs	20% of all possible O-D pairs
Number of Terminals (*V*)	2, 3, 4	2, 4
Number of Modes (*T*)	2, 3	2, 3
Discount Factor (α)	0.5, 0.9	0.5
Delay Factor (β)	1.2	1.2
Number of Potential Terminal Locations	100% of all nodes	10%, 15% and 20% of all nodes

4.5.2 Computational Results

Both, the Bender's decomposition algorithm and the preprocessing heuristic were implemented in MATLAB. All computational experiments were run on a 2.83 GHz Quad Core computer with 8 GB of RAM. The optimal solution for all instances in both Set A and Set B experiments were obtained using the Bender's decomposition approach. For each solution set, the trends that were observed in optimal solution costs for different parameter combinations will be presented first. Then, the performance of the Bender's decomposition approach and the preprocessing heuristic will be discussed and compared to the solution approach presented in Chapter 3.

4.5.2.1 Set A Computational Results

Set A experiments represent small instances of the integrated ILND problem. Table 4.2 shows the optimal solution costs for different experimental treatment combinations for one instance (i.e., Network Instance 1), and the percentage of the total cost that corresponds to the fixed cost of installing intermodal terminals. The exact same trends were observed in all other instances that were tested.

Similar to Chapter 3, the number of terminals in the intermodal logistics network should be determined prior to solving the problem using Bender's decomposition. Therefore, if the number of terminals is of interest by itself, the problem should be solved several times each time with a different number of terminals. Then, the optimal solutions associated with different number of terminals should be compared to each other to find the optimal number of terminals.

Table 4.2: Optimal solution costs for Network Instance 1 (Set A).

# of Nodes	# of Loads	Criteria	# of Modes = 2						# of Modes = 3					
			Discount Factor = 0.5			Discount Factor = 0.9			Discount Factor = 0.5			Discount Factor = 0.9		
			V = 2	V = 3	V = 4	V = 2	V = 3	V = 4	V = 2	V = 3	V = 4	V = 2	V = 3	V = 4
10	5 (5%)	Total Cost	503	610	722	514	622	736	503	610	722	514	622	736
		% Fixed Cost	46	56	63	41	52	61	46	56	63	41	52	61
	9 (10%)	Total Cost	781	884	991	781	888	998	781	884	991	781	888	998
		% Fixed Cost	33	41	48	33	41	49	33	41	48	33	41	49
	18 (20%)	Total Cost	1,390	1,467	1,565	1,390	1,481	1,579	1,390	1,467	1,565	1,390	1,481	1,579
		% Fixed Cost	20	26	33	20	26	32	20	26	33	20	26	32
	45 (50%)	Total Cost	3,118	3,113	3,172	3,150	3,176	3,241	3,118	3,113	3,172	3,150	3,176	3,241
		% Fixed Cost	8	12	16	8	12	16	8	12	16	8	12	16
20	19 (5%)	Total Cost	1,690	1,754	1,827	1,690	1,757	1,831	1,690	1,754	1,827	1,690	1,757	1,831
		% Fixed Cost	14	22	29	14	21	28	14	22	29	14	21	28
	38 (10%)	Total Cost	2,736	2,694	2,728	2,750	2,729	2,757	2,736	2,694	2,728	2,750	2,729	2,757
		% Fixed Cost	10	15	20	10	15	20	10	15	20	10	15	20
	76 (20%)	Total Cost	4,875	4,826	4,798	4,913	4,889	4,846	4,875	4,826	4,798	4,913	4,889	4,846
		% Fixed Cost	6	8	11	5	8	11	6	8	11	5	8	11
	190 (50%)	Total Cost	12,314	11,663	11,391	12,453	11,908	11,632	12,314	11,663	11,391	12,453	11,908	11,632
		% Fixed Cost	2	3	5	2	3	5	2	3	5	2	3	5
30	44 (5%)	Total Cost	2,984	2,857	2,789	3,029	2,927	2,893	2,984	2,857	2,789	3,029	2,927	2,893
		% Fixed Cost	7	11	17	7	11	16	7	11	17	7	11	16
	87 (10%)	Total Cost	4,921	4,679	4,654	4,931	4,720	4,675	4,921	4,679	4,654	4,931	4,720	4,675
		% Fixed Cost	4	7	10	4	7	10	4	7	10	4	7	10
	174 (20%)	Total Cost	10,477	9,931	9,559	10,518	10,093	9,796	10,477	9,931	9,559	10,518	10,093	9,796
		% Fixed Cost	2	4	5	2	4	5	2	4	5	2	4	5
	435 (50%)	Total Cost	27,040	25,517	24,380	27,185	25,868	24,850	27,040	25,517	24,380	27,185	25,868	24,850
		% Fixed Cost	1	1	2	1	1	2	1	1	2	1	1	2

According to Table 4.2, for a fixed network size, the optimal number of terminals depends on the number of loads in the network. When the number of loads is small, opening more terminals cannot reduce enough the total transportation cost to compensate for the additional fixed terminal installation costs. As a result, there would be a smaller number of terminals in the optimal network design. For example, for a network with 20 nodes and only 19 loads, the optimal cost of the network with two terminals is lower than the one with three or four terminals. On the other hand, when the network serves a larger number of loads, opening an additional terminal will increase the savings on transportation costs which will recoup what we pay for opening the additional terminal. For example, for the same network with 20 nodes and 190 loads, the optimal cost for the network with four terminals is less than the one obtained with two or three terminals.

Regarding the number of transportation modes, having more modes might help to reduce the transportation costs since more modes provide additional options when routing the freight loads. This is also shown in Table 4.2 where the optimal solution for the network with three transportation modes is always less than or equal to the one with two transportation modes.

Regarding the effect of consolidation on the optimal cost, it is expected that a larger discount factor would result in larger discounts and produce solutions with less optimal cost. This trend can also be observed in Table 4.2. On the other hand, it is expected that with a larger delay factor, freight loads would experience more delays at terminals which might make some routes infeasible with regards to the maximum allowed transportation time constraint. This will result in fewer options for routing freight loads which can increase the transportation cost. In other words, increasing the delay factor cannot improve the optimal solution but might worsen it.

Regarding the fixed cost of opening terminals, it can be seen in Table 4.2 that the percentage of the total network cost that corresponds to the fixed cost decreases as problem instances increased in size. The reason for this is that by increasing the number of freight loads in an instance, the total transportation cost increases to move the additional loads while the number of terminals remains the same. This reduces the share of total fixed cost of opening terminals in the total network costs. The exact same trend was observed in Set B instances.

To evaluate the performance of the proposed solution approach, the average solution time over five instances of the problem with the same experimental treatment combination were computed for solving the problem using Bender’s decomposition with and without the preprocessing heuristic. The average solution times were then compared to the average solution time obtained by applying the search algorithm presented in Chapter 3. The average solution times obtained when the preprocessing heuristic was applied prior to the Bender's decomposition algorithm (denoted ABD) and their percentage difference with respect to the other two approaches (i.e., Bender’s decomposition (BD) and SA) are presented in Table 4.3.

Table 4.3: Set A average solution times (in seconds) for accelerated Bender's decomposition (ABD) algorithm.

# of Nodes	# of Loads	Approach	# of Modes = 2						# of Modes = 3					
			Discount Factor = 0.5			Discount Factor = 0.9			Discount Factor = 0.5			Discount Factor = 0.9		
			# of Terminals			# of Terminals			# of Terminals			# of Terminals		
			2	**3**	**4**	**2**	**3**	**4**	**2**	**3**	**4**	**2**	**3**	**4**
10	**5**	**ABD**	0.006	0.002	0.002	0.001	0.001	0.006	0.002	0.004	0.004	0.000	0.004	0.001
		BD (%Diff.)	-56	-90	-96	-89	-96	-92	-79	-84	-94	-100	-82	-99
		SA (%Diff.)	-8	-20	-30	0	0	-5	-33	-33	-33	-100	-33	-67
	9	**ABD**	0.000	0.001	0.004	0.002	0.002	0.005	0.000	0.005	0.005	0.002	0.003	0.005
		BD (%Diff.)	-100	-96	-95	-79	-94	-94	-100	-80	-93	-68	-92	-94
		SA (%Diff.)	-100	0	-33	-33	-33	-17	-100	-17	-10	-67	-13	-25
	18	**ABD**	0.002	0.003	0.007	0.001	0.011	0.016	0.002	0.008	0.014	0.008	0.011	0.021
		BD (%Diff.)	-68	-93	-93	-84	-76	-83	-84	-79	-86	28	-75	-77
		SA (%Diff.)	-33	0	-22	-67	-31	-16	-33	-11	-13	-11	-8	-5
	45	**ABD**	0.012	0.025	0.047	0.015	0.030	0.080	0.019	0.041	0.084	0.015	0.040	0.010
		BD (%Diff.)	-33	-65	-71	-31	-56	-53	-25	-43	-47	-31	-47	-94
		SA (%Diff.)	-22	-43	-42	-6	-19	-8	-1	-19	-6	-6	-15	-91
20	**19**	**ABD**	0.012	0.025	0.056	0.022	0.053	0.197	0.012	0.041	0.109	0.022	0.106	0.427
		BD (%Diff.)	-73	-94	-98	-56	-87	-92	-71	-90	-95	-50	-73	-81
		SA (%Diff.)	-43	-75	-81	-1	-44	-43	-43	-61	-70	-1	-5	1
	38	**ABD**	0.044	0.228	0.986	0.056	0.387	1.894	0.047	0.315	1.526	0.072	0.462	2.518
		BD (%Diff.)	-50	-62	-71	-33	-36	-44	-40	-47	-56	-12	-26	-25
		SA (%Diff.)	-18	-31	-23	6	18	37	-25	-13	-1	28	21	53
	76	**ABD**	0.081	0.474	2.134	0.103	0.708	3.469	0.097	0.583	2.923	0.119	0.814	4.256
		BD (%Diff.)	-43	-54	-62	-23	-33	-38	-34	-45	-48	-21	-23	-25
		SA (%Diff.)	-32	-37	-40	-13	-7	-4	-21	-29	-29	-5	-3	1
	190	**ABD**	0.215	1.226	5.735	0.256	1.619	7.784	0.243	1.544	7.663	0.300	1.922	9.887
		BD (%Diff.)	-38	-49	-53	-25	-32	-37	-29	-36	-37	-9	-19	-19
		SA (%Diff.)	-28	-36	-38	-13	-16	-17	-20	-24	-27	-1	-8	-7
30	**44**	**ABD**	0.075	0.509	2.780	0.122	0.998	6.664	0.097	0.655	4.153	0.137	1.307	9.672
		BD (%Diff.)	-63	-80	-87	-42	-60	-69	-52	-73	-81	-34	-47	-55
		SA (%Diff.)	-52	-61	-63	-19	-26	-17	-36	-55	-53	-10	-13	1
	87	**ABD**	0.225	2.037	14.727	0.309	3.070	24.739	0.275	2.652	21.188	0.334	3.382	28.345
		BD (%Diff.)	-40	-52	-59	-15	-27	-30	-28	-37	-40	-12	-20	-20
		SA (%Diff.)	-27	-33	-35	1	0	7	-12	-20	-20	7	0	6
	174	**ABD**	0.402	3.435	23.594	0.555	5.310	41.503	0.462	4.249	31.802	0.608	6.290	51.976
		BD (%Diff.)	-47	-56	-64	-24	-32	-36	-38	-47	-52	-16	-21	-21
		SA (%Diff.)	-34	-44	-50	-9	-15	-13	-26	-36	-41	-3	-6	-4
	435	**ABD**	0.983	8.430	56.816	1.401	13.326	101.182	1.214	11.407	86.456	1.532	15.232	121.793
		BD (%Diff.)	-45	-56	-63	-21	-31	-34	-31	-41	-43	-15	-21	-21
		SA (%Diff.)	-35	-46	-53	-7	-16	-16	-22	-32	-36	-2	-9	-9

According to Table 4.3, the average solution time increases with the instance size (number of nodes, number of freight loads, and number of transportation modes that are integrated to form the intermodal logistics network). In addition to the instance size, the number of terminals in the network also had a significant effect on solution time. However, as expected, the value of the constant discount and delay factors had no significant effect on solution time. The accelerated Bender's decomposition approach outperforms both Bender's decomposition and the search algorithm presented in Chapter 3. However, it can be seen that the search algorithm of Chapter 3 has a better computational performance than the Bender's decomposition approach. The preprocessing heuristic applied prior to Bender's decomposition, improved its performance by decreasing the instance size and improving the upper bound. Tables 4.4 and 4.5 show the average percentage of discarded potential terminal locations and freight loads using the preprocessing heuristic, respectively.

Table 4.4: Average percentage of discarded potential terminal location using preprocessing heuristic in Set A instances.

# of Nodes	# of Loads	# of Modes 2		# of Modes 3	
		Discount Factor 0.5	**Discount Factor 0.9**	**Discount Factor 0.5**	**Discount Factor 0.9**
10	**5 (5%)**	60	40	58	40
	9 (10%)	48	30	38	28
	18 (20%)	25	10	13	8
	45 (50%)	18	0	5	0
20	**19 (5%)**	61	44	56	35
	38 (10%)	16	6	14	3
	76 (20%)	10	3	6	3
	190 (50%)	4	1	1	0
30	**44 (5%)**	33	18	29	13
	87 (10%)	10	0	5	1
	174 (20%)	11	2	7	0
	435 (50%)	11	1	4	0

According to Table 4.4, the average number of discarded potential terminal locations decreases as the number of freight loads in the network increases. As mentioned in Section 4.4.3.4, the preprocessing heuristic discards a potential terminal location when no freight load uses it even in the case when all terminals would be open. Therefore, as more freight loads exist there is a higher chance that a potential terminal location will be used. If in addition to discarding the unused locations, the preprocessing heuristic also discards potential locations that would be used only a few times, fewer potential locations would result in shorter solution times. However, this might reduce the quality of solutions (i.e., the procedure might not get the optimal solution).

Also regarding instance size reduction by applying the preprocessing heuristic, it can be seen in Table 4.5 that about 20% to 30% of freight loads were discarded from further exploration because they are were routed point-to-point even when all terminals were open. Similar results were observed for Set B instances.

Table 4.5: Average percentage of discarded freight loads using preprocessing heuristic in Set A instances.

# of Nodes	# of Loads	# of Modes 2		# of Modes 3	
		Discount Factor 0.5	Discount Factor 0.9	Discount Factor 0.5	Discount Factor 0.9
10	5 (5%)	40	25	30	15
	9 (10%)	44	33	36	19
	18 (20%)	35	19	29	11
	45 (50%)	49	36	44	26
20	19 (5%)	50	41	45	36
	38 (10%)	31	20	28	18
	76 (20%)	38	28	36	22
	190 (50%)	36	26	34	20
30	44 (5%)	31	22	31	20
	87 (10%)	29	19	29	16
	174 (20%)	31	23	29	19
	435 (50%)	31	22	29	17

4.5.2.2 Set B Computational Results

Table 4.6 shows the optimal solution costs for Network Instance 1 for all experimental treatment combinations in Set B and the percentage of the fixed cost in the total solution cost. In addition to the trends discussed in Section 4.5.2.1, it can be observed that the optimal solution was affected by the number of potential terminal locations that were considered in the integrated ILND problem. More potential terminal locations means more options for locating intermodal terminals. These additional options can reduce the total solution cost. In other words, increasing the number of potential terminal location cannot worsen the optimal solution but it might improve it.

Also, Table 4.7 shows the average solution times over five instances of each experimental treatment combination in Set B for the accelerated Bender's decomposition. Table 4.7 also shows the percentage difference in average solution time of the accelerated Bender's decomposition approach with respect to Bender's decomposition and the search algorithm presented in Chapter 3. Similar trends to those observed for Set A instances were found for Set B instances. Moreover, the solution time was also affected by the number of potential terminal locations. More potential terminal locations result in a bigger solution space which would require more time to find optimal solutions. Note that the search algorithm presented in Chapter 3 was tested with instances having up to 150 nodes and 4,470 freight loads, therefore the percentage differences shown in Table 4.7 were calculated only for those instances. Similar to Set A instances, the accelerated Bender's decomposition approach outperforms the other two approaches as seen in Table 4.7. The largest problem instances with 250 nodes, 50 potential terminal locations, and 12,450 freight loads were solved in about 5 hours in average, which is reasonable for a strategic planning problem such as the integrated ILND problem.

Table 4.6: Optimal solution costs for Network Instance 1 (Set B).

# of Nodes	# of Loads	# of Potential Terminal Locations	Approach	Discount Factor = 0.5			
				# of Modes = 2		# of Modes = 3	
				V = 2	V = 4	V = 2	V = 4
50	**490 (20%)**	**10% *N***	Total Cost	31,629	30,945	31,629	30,945
			% Fixed Cost	0.74	1.53	0.74	1.53
		15% *N*	Total Cost	31,091	29,141	31,091	29,141
			% Fixed Cost	0.89	1.81	0.89	1.81
		20% *N*	Total Cost	31,091	29,141	31,091	29,141
			% Fixed Cost	0.89	1.81	0.89	1.81
75	**1110 (20%)**	**10% *N***	Total Cost	69,977	65,670	69,977	65,670
			% Fixed Cost	0.39	0.78	0.39	0.78
		15% *N*	Total Cost	69,459	64,907	69,459	64,907
			% Fixed Cost	0.34	0.78	0.34	0.78
		20% *N*	Total Cost	68,569	63,334	68,569	63,334
			% Fixed Cost	0.37	0.76	0.37	0.76
100	**1980 (20%)**	**10% *N***	Total Cost	126,337	116,840	126,337	116,840
			% Fixed Cost	0.22	0.46	0.22	0.46
		15% *N*	Total Cost	126,337	115,605	126,337	115,605
			% Fixed Cost	0.22	0.45	0.22	0.45
		20% *N*	Total Cost	125,842	115,605	125,842	115,605
			% Fixed Cost	0.22	0.45	0.22	0.45
150	**4470 (20%)**	**10% *N***	Total Cost	286,296	270,144	286,296	270,144
			% Fixed Cost	0.09	0.20	0.09	0.20
		15% *N*	Total Cost	286,296	264,380	286,296	264,380
			% Fixed Cost	0.09	0.19	0.09	0.19
		20% *N*	Total Cost	286,296	264,380	286,296	264,380
			% Fixed Cost	0.09	0.19	0.09	0.19
200	**7960 (20%)**	**10% *N***	Total Cost	511,477	473,557	511,477	473,557
			% Fixed Cost	0.05	0.11	0.05	0.11
		15% *N*	Total Cost	505,460	466,178	505,460	466,178
			% Fixed Cost	0.05	0.11	0.05	0.11
		20% *N*	Total Cost	505,460	461,624	505,460	461,624
			% Fixed Cost	0.05	0.11	0.05	0.11
250	**12,450 (20%)**	**10% *N***	Total Cost	802,942	746,029	802,942	746,029
			% Fixed Cost	0.02	0.05	0.02	0.05
		15% *N*	Total Cost	802,942	737,342	802,942	737,326
			% Fixed Cost	0.02	0.05	0.02	0.05
		20% *N*	Total Cost	802,942	736,896	802,550	736,099
			% Fixed Cost	0.02	0.05	0.02	0.05

Table 4.7: Set B average solution times (in seconds) for ABD algorithm.

# of Nodes	# of Loads	# of Potential Terminal Locations	Approach	Discount Factor = 0.5			
				# of Modes = 2		# of Modes = 3	
				V = 2	V = 4	V = 2	V = 4
50	490 (20%)	10% *N*	ABD	0.02	0.02	0.02	0.02
			BD (%Diff.)	-43	-33	-33	-27
			SA (%Diff.)	0	-60	-19	-43
		15% *N*	ABD	0.07	0.21	0.08	0.24
			BD (%Diff.)	-46	-52	-37	-43
			SA (%Diff.)	-41	-43	-32	-41
		20% *N*	ABD	0.12	0.66	0.13	0.75
			BD (%Diff.)	-38	-48	-32	-41
			SA (%Diff.)	-32	-39	-30	-38
75	1110 (20%)	10% *N*	ABD	0.16	0.44	0.17	0.51
			BD (%Diff.)	-44	-53	-37	-46
			SA (%Diff.)	-38	-45	-36	-43
		15% *N*	ABD	0.33	2.28	0.35	2.60
			BD (%Diff.)	-40	-48	-35	-40
			SA (%Diff.)	-33	-40	-35	-39
		20% *N*	ABD	0.69	10.43	0.74	11.71
			BD (%Diff.)	-32	-42	-28	-35
			SA (%Diff.)	-26	-33	-24	-33
100	1980 (20%)	10% *N*	ABD	0.48	2.56	0.51	2.86
			BD (%Diff.)	-39	-48	-33	-41
			SA (%Diff.)	-33	-41	-33	-40
		15% *N*	ABD	1.22	18.60	1.31	20.92
			BD (%Diff.)	-32	-41	-27	-34
			SA (%Diff.)	-27	-33	-25	-32
		20% *N*	ABD	2.23	62.75	2.52	79.49
			BD (%Diff.)	-31	-44	-23	-29
			SA (%Diff.)	-26	-36	-19	-26
150	4470 (20%)	10% *N*	ABD	2.72	40.66	2.87	45.42
			BD (%Diff.)	-33	-43	-29	-36
			SA (%Diff.)	-27	-34	-27	-35
		15% *N*	ABD	7.08	285.19	7.47	318.21
			BD (%Diff.)	-28	-38	-23	-31
			SA (%Diff.)	-21	-29	-21	-30
		20% *N*	ABD	12.41	883.75	13.08	989.68
			BD (%Diff.)	-26	-38	-22	-31
			SA (%Diff.)	-20	-29	-20	-29
200	7960 (20%)	10% *N*	ABD	9.25	272.93	9.76	305.89
			BD (%Diff.)	-29	-39	-25	-32
			SA (%Diff.)	-	-	-	--
		15% *N*	ABD	22.75	1,658.16	24.06	1,902.03
			BD (%Diff.)	-24	-35	-19	-25
			SA (%Diff.)	-	-	-	-
		20% *N*	ABD	40.30	5,086.59	42.40	5,806.03
			BD (%Diff.)	-25	-40	-21	-32
			SA (%Diff.)	-	-	-	-
250	12450 (20%)	10% *N*	ABD	23.53	1,166.19	25.52	1,331.04
			BD (%Diff.)	-27	-36	-19	-27
			SA (%Diff.)	-	-	-	-
		15% *N*	ABD	54.68	6,196.35	58.84	7,102.16
			BD (%Diff.)	-26	-42	-21	-33
			SA (%Diff.)	-	-	-	-
		20% *N*	ABD	87.92	15,757.61	97.82	18,830.26
			BD (%Diff.)	-32	-53	-25	-44
			SA (%Diff.)	-	-	-	

A summary of all of the trends observed in the computational results for both Set A and Set B instances is presented in Table 4.8.

Table 4.8: Summary of observed trends in the results for both Set A and Set B instances.

Change	**Solution Cost**	**Solution Time**
Increasing number of nodes	Increase	Increase
Increasing number of freight loads	Increase	Increase
Increasing number of potential terminal locations	Decrease	Increase
Increasing number of transportation modes	Decrease	Increase
Increasing discount factor	Decrease	No change
Increasing delay factor	Increase	No change

4.6 Conclusions and Future Work

The expected growth of intermodal transportation demand along with the reduced environmental and social costs associated with intermodal transportation make the problem of locating new intermodal facilities more important every day. Recently, relevant tactical and operational decisions including route and mode selection for freight loads have been integrated with the intermodal terminal location problem in order to improve the performance of the intermodal logistics network. However, integrating all of these decisions in a single mathematical formulation adds complexity and makes it more difficult to find optimal solutions in an efficient way. In this research, a Bender's decomposition algorithm is implemented to solve the integrated ILND problem as formulated Chapter 3. A preprocessing heuristic was also developed that reduces the problem instance size and obtains better upper bounds for the problem. Based on the results obtained in the computational experiments, the preprocessing heuristic was able to improve the performance of the Bender's decomposition algorithm significantly.

The computational results show that the optimal solution cost significantly depends on the number of nodes, freight loads, potential terminal locations, number of transportation modes in the network, and the value of discount and delay factors for consolidated movements. Moreover, the computational time of the accelerated Bender's decomposition approach depends on the number of nodes, freight loads, potential terminal locations, number of terminal locations to open, and transportation modes in the network. The accelerated Bender's decomposition approach was able to obtain the optimal solution for a large instance of up to 250 nodes and 12,450 freight loads in about 5 hours which is reasonable time for the strategic integrated ILND problem. As a potential area of improvement, a parallel computing implementation of the formulation and solution method can be implemented to further reduce the computational time.

Another future research direction could be the integration of additional related decisions such as imposing a resource level limitation at terminals within the integrated ILND problem. This would certainly increase the complexity of the formulation of the integrated ILND problem, but will result in a more realistic model. Also, a more realistic assumption could be considered especially for modeling the effect of consolidation on transportation cost and time for inter-terminal movements as opposed to using constant discount and delay factors. The latter two research directions would improve the applicability of the resulting intermodal logistics networks obtained for the integrated ILND problem in practice, but on the other hand would increase the complexity of the mathematical formulation. Consequently, additional work on developing efficient solution methods to solve this large-scale optimization problem is also an area for future research.

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4.8 Appendix B

Proposition 1: If the optimal route for a freight load is point-to-point when all potential intermodal terminals are open, then the optimal route for this load in the optimal network design (when only terminals at the optimal locations are open) would be point-to-point as well.

Proof by contradiction:

Suppose the optimal route for this load in the optimal network design is denoted by R_l^* and R_l^* is not point-to-point, this means R_l^* passes through at least one open terminal. Since R_l^* is the optimal route, the transportation cost of R_l^* is less than the transportation cost of the point-to-point route. Since all the terminals that R_l^* passes through would be open in the solution when all terminals are open, R_l^* would be available in that scenario. Therefore, there would be another feasible route available with lower transportation cost when all terminals were open which is in contradiction with the fact that the optimal route for this load was point-to-point when all terminals were open. ■

Proposition 2: If a potential location is never used in any of the optimal routes when all terminals were open; this potential location would be close in the optimal network.

Proof:

Suppose potential location k is never used in any of the optimal routes when all terminals were open. Therefore, opening a terminal at location k won't change any optimal route which means we won't get any additional savings on transportation cost. On the other hand, opening a terminal at k would increase the fixed installation cost by F_k. As a result, opening a terminal at k would increase the objective function which is in contradiction with minimizing the objective function. ■

5 Conclusions and Future Work

The expected growth of intermodal transportation demand along with the reduced environmental and social costs associated with intermodal transportation make the problem of locating new intermodal facilities more relevant every day. This research addressed the problem of designing intermodal logistics networks by developing two mathematical formulations in which the route and mode selection problems are integrated with the problem of finding the best location for new intermodal transportation facilities. The arc-based formulation presented in Section 2.4.2, considered a nonlinear cost function that relates the per container transportation cost to the amount of flow between two nodes. Although this is a realistic assumption, modeling it this way made the mathematical formulation intractable even for medium size instances of the problem. So, in order to obtain near optimal solutions for this arc-based solution, a GA-based heuristic approach that combines a genetic algorithm and the shortest path algorithm was developed. According to the computational experiments performed with this formulation and solution approach, the proposed GA-based heuristic was able to obtain solutions that were very close to the optimal solution for small instances of the problem with 10 nodes. More importantly, the GA-based heuristic was able to find most of the optimal intermodal terminal locations. However, the percentage cost difference between the GA-based heuristic solution and optimal solutions increased with the size of the instances. Still, the average percentage of optimal hubs found by the GA-based heuristic was large even as instance sizes increased. The latter shows that the difference between the total cost obtained using the GA-based heuristic method and the optimal solution was due to the selection of non-optimal routes and transportation modes by the proposed GA-based heuristic. Therefore, improving the load route and transportation mode selection portion of the GA-based heuristic approach is a potential area for future research.

Although we obtained heuristic solutions that were very close to the optimal solutions for small instances of this formulation, we were not able to obtain the optimality gap for larger instances. Therefore, another potential area for future research could be developing and implementing a lower bound approach such as Lagrangian relaxation to obtain high quality lower bounds for the arc-based mathematical formulation. These lower bounds then can be used to guarantee small optimality gaps for the proposed GA-based heuristic solutions.

Since, the arc-based mathematical formulation was shown to be intractable for even medium instances of the IILND problem; a route-based formulation was developed. This formulation takes advantage of composite variables to capture route feasibility constraints within the formulation of the variables instead of explicitly including them in the mathematical model. Moreover, unlike the arc-based formulation, the effects of consolidating freight loads at intermodal terminals on transportation cost and time were modeled using constant discount and delay factors, respectively. A decomposition-based search algorithm was developed to obtain the optimal solution of the proposed route-based formulation with composite variables. According to the computational experiments, the computational time required to obtain optimal solutions using the decomposition-based search algorithm increased with the size of instances, number of potential intermodal terminal locations, and number of open intermodal terminals in the network. For example, it took about 25 minutes to find the optimal solution for an instance with 150 nodes and 4,500 freight loads when locating four intermodal terminals. The decomposition-based search algorithm showed good performance for small and medium size instances of the IILND problem. However, in order to obtain optimal designs for real size intermodal logistics networks, an accelerated Bender's decomposition algorithm was developed which can solve large instances of up to 250 nodes and 12,450 freight loads in about five hours when locating four intermodal terminals. According to the completed computational experiments for both solutions approaches that were developed to find the optimal solution of the route-based mathematical formulation, the optimal solution costs depends on the network size (i.e., number of nodes and loads, and the number of transportation modes), number of hubs to be opened, and the value of the discount and delay factors that are applied to the inter-hub transportation cost and time.

The objective function of both mathematical formulations that were presented in this research was to minimize the total network costs including the fixed terminal installation costs and the total transportation cost associated with the freight loads. However, the applicability of this research can be increased by considering other costs related to intermodal transportation networks including a cost due to conflicts of interest between different stakeholders engaged in the intermodal transportation network (i.e., carriers of each of the single mode networks, shippers, terminal operators, etc.) or environmental costs associated with the logistics network including the greenhouse gas emissions costs. Incorporating these cost elements to the objective function of the IILND problem would be another potential area for future research.

Finally, the applicability of the proposed mathematical formulations can also be improved by integrating more related decisions to the IILND problem including resource levels at intermodal terminals (i.e., workforce levels, number and type of cranes and other material handling and storage equipment, etc.) which are required based on expected freight traffic flow through the terminals, intermodal terminal layout, etc. Note that integrating more related decision will improve the applicability of a mathematical formulation for the IILND problem, but on the other hand, it will increase the complexity of the formulation as well. Therefore, new efficient solution approaches are also needed for new integrated mathematical formulations of this problem. Otherwise, the new mathematical formulation might not be useful to solve real size instances of the IILND problem.

Furthermore, during this research I had the opportunity to learn many operations research and computer science techniques that can be applied to large-scale optimization problems. These type of problems are very interesting to me.

Therefore, I want to do more research to apply these and other operations research and computer science techniques to other practical problems including different problems within the supply chain industry. Specifically, I would like to apply learning algorithms to obtain good solutions for integrated supply chain planning problems which would be an interesting field of study for future research.

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