# TOOL TO ASSESS EFFECTIVENESS OF INTERMODAL FACILITY LOCATION AND CARRIER COLLABORATION

**Final Report**

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## Center for Connected Multimodal Mobility ($C^2M^2$)

**Center for Connected Multimodal Mobility ($C^2M^2$)**


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### 16. Abstract

This study is focused on the design and operation of a freight network that supports carrier collaboration where two or more carriers form an alliance and share pick-up and delivery of jobs. In carrier collaboration, it is assumed that carriers can retain some of the pickup and delivery jobs they receive from clients while releasing the rest of the jobs to a common pool. A two-stage model and framework for the application of this model in the real-world are developed. The stage-1 model is for strategic planning and the stage-2 model is for operational planning. The strategic model uses demand forecasts to determine the intermodal terminal (IMT) locations and provides the pickup and delivery jobs to the operational model. The strategic model is used for long term planning, whereas the operational model is used for short term planning. The realized/actual shipping data from the operational model can provide feedback to the forecasting model to update supply and demand forecasts. The updated supply and demand forecasts are used to re-evaluate the long-term plan by opening or closing IMT locations as deemed necessary by the decision makers. The objective of the multi-period strategic model is to determine the number and location of IMTs that minimize the total relevant transportation and operational costs. The objective of the operational model is to jointly determine the optimal allocation of jobs from the common pool to the carriers and pickup/delivery routes for each truck. Numerical experiments are conducted using hypothetical networks for both models. Findings from the strategic model show regions with higher supply or demand of freight volume tend to have higher utilized IMTs and impact the total network cost the most. The sensitivity analysis for budget shows that intermodal shipping share and total network cost converge at a point and the model does not add new IMTs. The alternate optimal solutions show the tradeoff between intermodal shipping share and total network cost with budget investment in opening IMTs. Findings from the operational model confirm the expectation that carrier collaboration can yield a significant reduction in the total cost of serving all pickup and delivery jobs. The cost savings from the collaboration is dependent on the spatial distribution of the nodes in the network, network size, the distance between carrier depots, percentage of pooled jobs, size of the overlapping region of carriers, and the number of jobs in the overlapping region.


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# EXECUTIVE SUMMARY

This project focuses on the development of a tool to help decision makers improve the inefficiencies in the current freight transportation system. Increased transportation costs, empty truck hauls, and lack of synergy between different modes of transport are some of the critical factors that contribute to these inefficiencies. Two aspects of this problem are addressed: 1) locating intermodal terminals (IMT) in a collaborative freight transportation network and 2) improving the regional pickup and delivery services through less than truckload (LTL) carrier collaboration. A two-stage model is developed to address this problem. The first stage strategic model decides the intermodal terminal locations and freight flows over longer distances and the second stage operational model decides the collaborative vehicle routes to reduce the cost\distance of transportation from the consolidation centers to the customers (or vice versa). The strategic model determines the number and location of IMTs that minimize the total relevant transportation and operational costs. Constraints on this model reflect key features in reality like ensuring all pickup/delivery demands to/from customers are met, operating under a limited budget, and selecting from among a limited set of candidate IMT locations. The operational model assumes that the carriers collaborate by sharing their pickup and delivery jobs and determines the optimal reassignments of these jobs to the carriers by finding the optimal vehicle routes to serve the jobs. The key real-world constraints embedded in this model are: carriers can designate some jobs to be retained by that carrier while others are sent to a common pool for sharing, time window at each pickup/delivery location, vehicle capacity, and the restriction on the maximum hour in one vehicle route. A framework is developed for the application of this two-stage model over a rolling horizon. For the planning horizon forecasted, supply and demand are provided to the first stage model which decides the forecasted jobs for the second stage model to be carried out. To tackle the uncertainty in forecasted supply and demands, the actual supply and demand data from the second stage model can be used to develop a better forecast for the first stage model.

Strategic model for locating intermodal terminals

A case study is conducted on the state of South Carolina using public data sets to test the model. The State is divided into five regional zones that are developed by utilizing regional map divisions, and the Freight Analysis Framework (FAF) zones. The potential IMT facilities are located at major road and rail intersections across the State and at existing intermodal facilities. The case study uses data from 2017 and a planning horizon of 12 months that is divided into 12, one-month periods. The results show that an IMT in Columbia is quite important. When the Columbia IMT is removed and the model has resolved the total network cost increases by 17%, intermodal shipping share decreases by 16%, and the average direct shipping distance increases by 39%. Sensitivity analysis reveals the nonlinear trend between total network cost and budget. It could impact decision-makers because it allows them to quantitatively evaluate the benefits associated with increasing budget levels and use this information to support budget requests. By incrementally increasing the number of IMT's and dissecting the solution, insight is gained on the locations that have the most significant impact on cost as well as cost comparisons between scenarios and against the base-case scenario. The solutions for less than 6, 7, 8, 9, and 10 IMTs resulted in modest improvement with the increase in total network cost at most 6% above optimal (11 IMTs) and saving in expenditure on fixed cost up to 45% from optimal (11 IMTs). To counter the excessive demand for mixed freight in October (1.75 times), November (2 times) and December (2.5 times), inventory at an IMT acts as a buffer and reduces or eliminates any negative impact associated with it. Since 72%

of the total demand for mixed freight is in the upper geographical region of the state, the model builds 95% of the total inventory in this region. The highest volume of freight is held at Greenville (29%), followed by Spartanburg (27.5%), and Florence (17.7%).

Operational model for carrier collaboration

Collaboration between LTL carriers is considered as horizontal collaboration in which the organizations at the same level in a supply chain collaborate to improve efficiency and reduce costs. This work adopts the commonly used centralized, collaborative planning scheme where a central authority pools all jobs and allocates them to the carriers to minimize the total transportation cost. However, LTL carriers can retain some of the jobs. A mathematical model is developed to determine the optimal allocation of jobs to the carriers by finding the optimal pickup/delivery routes for each truck. Results from computational analyses show that there are significant cost savings when carriers collaborate, but it is dependent on several factors such as the spatial distribution of the nodes in the network, network size, the distance between carrier depots, percentage of pooled jobs, size of the overlapping region of carriers and the number of jobs in the overlapping region. The cost savings, when carriers retain some of their jobs, is smaller than that when carriers pool all jobs, but it is higher than that of non-collaboration. Therefore, allowing carriers to retain some jobs is beneficial as it encourages collaboration participation. In addition, the increase in cost savings concerning the pooled jobs and size of the overlapping region is non-linear; significant benefits can be achieved through relatively small collaboration efforts by the carriers.

# CHAPTER 1
# Introduction

The demand for freight transportation is increasing drastically and is expected to grow to 27.5 billion tons in 2040 (Grenzeback et al., 2013). The increase in demand leads to several negative externalities such as congestion, pollution, infrastructure damages, road accidents, etc. Intermodal transportation which consists of at least two modes of transportation has been considered as a solution to mitigate these negative externalities (Arnold et al., 2004). However, the efficiency of intermodal transportation depends on the location and number of intermodal terminals. Improper location of terminals increases the operation cost and an incorrect number of terminals leave the network underutilized or overloaded. In addition, the pre and end haulage of intermodal transportation (origin to an intermodal terminal and from intermodal terminal to destination) is done by trucks. Therefore, adopting strategies to improve truck transportation is also crucial. This study proposes a two-stage solution to effectively improve intermodal freight transportation. The first stage deals with the efficient transfer of freight between different modes at intermodal terminals (IMT) and the second stage deals with collaboration among less than truckload (LTL) carriers to improve the efficiency of truck transportation. The first stage is strategic and the second stage is operational. The following paragraphs explain the two stages in detail.

Opening an intermodal facility involves an initial setup cost, operational costs, material handling costs, etc. Groothedde et al. (2005) consider direct trucking to be essential for short distances and to be able to handle excess demand that cannot be met through the intermodal network. There is a trade-off between the availability and flexibility of direct trucking and the economies of scale of intermodal shipping. Another crucial factor to be considered when designing a network is the dynamic aspect of the Intermodal Terminal Location Problem (IMTLP). Costs, capacities, and demands are all dynamic. Multi-period planning provides the opportunity to systematically invest capital over multiple periods. For example, the decision-maker must have the ability to open a terminal at any time, not just in the first period. According to Fotuhi and Huynh (2018) the multi-period approach benefits the stakeholder as: (i) it reduces the burden financially to expand the network over a short period, (ii) it helps in managing resources better by opening IMTs "just-in-time", and (iii) it improves the routing decisions for different periods due to better resource utilization. Extreme weather can impact certain modes of transportation and multi-period modeling can avoid these modes in the problematic periods of the planning horizon. The intermodal freight network is ever-changing (e.g. Panama Canal expansion), and these changes can be included in a multi-period model.

Independent carriers receive pick up and delivery jobs from shippers and consignees, and they serve these jobs most cost-effectively (i.e., they seek the least-cost routes). When carriers can share their jobs with other carriers, they could potentially reduce their respective costs and negative externalities (Pérez-Bernabeu et al., 2015). This form of job sharing is considered horizontal collaboration where organizations at the same echelon in a supply chain collaborate (Ferrell et al., 2019). It's different from vertical collaboration where organizations at different levels in a supply chain collaborate, such as collaboration between manufacturers, shippers, and carriers (Ergun, et al., 2007). Vertical collaboration has been used for some time, especially by large companies that have established relationships with suppliers and transportation partners; Walmart and Toyota are two commonly cited examples (Li and Maani, 2011). Horizontal collaboration, on the other hand, is an emerging trend in logistics, and it is becoming more relevant in practice (Cruijssen et al., 2007).

There are two structural approaches for carrier collaboration: decentralized planning and centralized planning (Gansterer and Hartl, 2017). In the decentralized collaborative planning approach, each carrier makes its own decision regarding how they want to collaborate. This approach gives carriers flexibility and allows them to operate independently (Li et al., 2015). On the other hand, in the centralized collaborative planning approach, a central authority pools all jobs and makes the job allocation decisions on behalf of the carriers (Gansterer and Hartl, 2017). The key to the centralized planning approach is that all information necessary to make the decisions (it includes details about the carriers and shipments) is shared with the central authority. The central authority can either be a third party or a large carrier who manages the job allocation in an unbiased manner (Dai and Chen, 2012). The centralized planning approach has been shown to provide more benefits than the decentralized planning approach (Berger and Bierwirth, 2010). However, in practice, carriers would most likely want to retain those jobs that can be served easily, are most profitable, or are from strategic customers. In such a system, carriers still receive jobs and they are allowed to retain some number for themselves; however, the remainder is aggregated in a common pool from which a central authority determines the optimal allocation for each carrier. The jobs in the common pool can be optimally allocated to the carrier by determining the optimal routes for each carrier to serve both retained and allocated jobs.

The objective of this study is to develop a two-stage model to enable the evaluation of single and/or multi-modal facilities and the necessary collaboration scheme between carriers. The strategic model in the first stage determines the number and location of IMTs that minimize the total relevant transportation and operational costs, given a set of constraints like ensuring all pickup/delivery demands to/from customers are met, budget, and a limited set of candidate IMT locations jobs (model is referred to as Intermodal terminal location problem, IMTLP hereafter). The operational model in the second stage determines the optimal allocation of pooled jobs to each carrier in the alliance by determining the optimal routes to serve both retained and allocated jobs (model is referred to as carrier collaboration vehicle routing problem with pickup and delivery, CCVRPPD hereafter).

The next chapter (Chapter 2) presents a literature review of related work. Chapter 3 describes the two-stage model. Chapter 4 presents the methodology and results of the strategic model. Chapter 5 presents the methodology and results of the operational model. Lastly, Chapter 6 presents this study's summary and conclusions.

# CHAPTER 2
# Literature Review

A detailed literature review of the intermodal terminal and carrier collaboration is done in this section. The type, design, and location of IMT are the major factors affecting the operational efficiency of intermodal transportation, (Allen et al., 2012, Bontekoning, 2000). Therefore, the literature review on intermodal transportation has been done in two sections: (i) study on types of intermodal terminals and their design characteristics, (ii) literature review of optimal IMT location problems.

## 2.1 Types of intermodal terminals and their design characteristics

A background study on types, factors influencing the type and design, and the transshipment requirements of the intermodal terminals are provided in this section.

Based on location and the requirements of equipment, the intermodal terminals are classified into three categories such as a port terminal, inland rail terminal, and distribution centers. A port terminal can be either a container sea terminal, an intermediate hub terminal, or a barge terminal. There are five different types of rail intermodal terminals such as on-dock, near dock, trans-modal terminal, load center, and satellite terminal. There are three different types of distribution centers such as transloading, cross-docking, and warehousing. See (Rodrigue et al., 2016) and ( Notteboom et al., 2018) for more information about each type of intermodal terminal.

Middendorf (1998) discussed various factors governing the classification and types of intermodal terminals. The authors state the intermodal terminals can be grouped into six according to the five dimensions such as mode pairs, type of cargo, type of transfer, private or public ownership, and availability for public use. They are trailer-on-flatcar/container-on-flatcar, auto terminal, truck-rail bulk transloading facilities, truck-rail reload facilities, liquid bulk terminals, grain terminals, and waterway intermodal terminals.

Based on the function of a terminal in the intermodal network, the intermodal railroad researchers identified four types of rail-road intermodal terminals (Behrends, 2011). They are start and end terminals, intermediate terminals, hub terminals, and spoke terminals. The start and end terminal usually handles a large volume of freight, which are split into smaller flows for further transport on road, however, the performance requirements on the transshipment technology are moderate. Intermediate terminals handle only a limited number of unit-loads which must be distributed at the terminal region. Here the demand for improvement in the transshipment technology is comparably high. Hub terminals are not intermodal terminals instead it provides transshipment of loads between different trains. Both the transshipment capacity and technology are very important in hub terminals because this terminal handles extensive throughput of unit loads. The spoke terminal consolidated small volumes of load units into bigger flows. However, the total load units handled are limited therefore, the transshipment technology requirements are comparatively low.

Woxenius (2007) studied how the transportation network design influencing the type, design, capacity requirements, and choice of transshipment technology at rail-road IMT. They described how the aforementioned varies with the most common six alternative transport network designs (direct link, corridor, hub-and-spoke, connected hubs, static routes, and dynamic routes). The suggested terminal types for each type of network are: for the direct link design, end terminal is suitable however, end terminal and intermediate terminal are suitable for corridor link design. Hub terminal and spoke terminal are suitable for both hub-and-spoke and connected hub design. Exchange terminal and gateway are suitable for static routes design. For dynamic routes, the suitable type of terminal is the exchange terminal.

The design requirements for terminals correspond to each transport network type of which there are several (Woxenius, 2007). In *direct link design*, all unit loads in the train are transshipped thus the terminal capacity requirement is limited. This design is complicated because of the large number of unit loads handled at the terminal. In *corridor design*, the number of unit loads handled is limited; therefore, the capacity requirement is moderate. The design objective here is that the transfer time should be minimum. Providing optional storage space in this design can be effective as well. The design of a terminal should be optimally decided to simultaneously provide fast transfer and minimum fixed cost. In *hub-and-spoke design*, all unit loads pass through the hub terminal; hence, the hub terminal requires a large capacity. Further, the whole system is adversely impacted if the hub terminal is not reliable. As might be expected, there is a great need for intermediate storage. In *connected hubs design,* only a limited number of trains are connected through the hubs so the capacity requirements are moderate. Static routes are often used for intermodal transport or when time demands are flexible. If the terminal along the static routes is not a gateway terminal, the transshipment capacity required is limited. In dynamic routes, the terminal requirements are like static routes. However, there is a greater need for flexibility as the operations change between each transport cycle.

Intermodal transportation is the widely preferred option for inland freight distribution due to its large capacity, less energy consumption, low cost, contribution to reducing road congestion, and environmental reasons (Zumerchik et al., 2012). However, the transfer delay at IMT would lead to the overall delay in product delivery, missing connections, and damage to products. With a substantial improvement in the IMT design and operations, the operational performance of the IMT can be greatly enhanced, (Rodrigue et al., 2009). The author says that the goods movement will remain dominantly serviced by trucking over increasingly congested highways if substantial improvements are not made to intermodal transportation. Quick handling time at the terminals will give more time at the link which improves the efficiency of freight transportation. All the above-mentioned facts show the necessity of improving the performance of IMT.

Only a few studies have been published that assess the ability of technologies to improve the operational performance of IMTs. Bontekoning (2000) discussed several new generation terminal designs which can significantly reduce the transfer delay at terminals and thereby reduce the total time and cost of intermodal freight transportation. Bontekoning et. al. (Bontekoning & Kreutzberger, 1999) defined the new generation terminal as the terminal which uses automation and robotization, integrated operations. and compact layout. The new generation terminal and new rail transshipment technologies make intermodal freight transportation more competitive. This research also listed several rail-road terminal design concepts that can be considered as new generation terminals. They are: (i) Noell Megahub, (ii) Commutor, (iii) Krupp Rendezvouz terminals Megahub, Highrack, Compact, and Small, (iv) Noel1 SUT 1200 and SUT 400, (v) Transmann Handling Machine, (vi) Tuchschmid Compact Terminals. Finally, the study noted the advantages of new generation terminals over conventional terminals. These include a reduction in the transshipment cost (and time) due to more efficient operations and a reduction in the costs (and time) on the link due to more sophisticated bundling.

Zumerchik et al. (2012) argued that an Automated Transfer Management System (ATMS) at terminals could significantly improve operational efficiency and economics of both long haul and short haul intermodal movements, including port shuttle trains. ATMS helps to provide better synchronization of multiple modes having different operational and technical characteristics. Application of ATMS at intermodal terminal includes, trackside at rail terminal, vessel loading /unloading, chassis flip, port stack container yards, chassis storage, and loading bays at distribution centers.

Several marine terminals have been converted into automated terminals worldwide. The Rotterdam marine terminal is the first automated terminal that is opened in 1993 (Port automation, 2018). Now the largest automated terminal started operation in Shanghai, China (Largest Automated Container Terminal Starts Operations, 2018).

## 2.2 Models for locating intermodal terminals

The literature on facility location is extensive so this review focuses on that which is most relevant to intermodal transportation and the nature of this research. According to Teye et al. (2017), IMTLP can be considered as an extension of the classical Hub Facility Location Problems (HFLP). The HFLP first gained attention with the seminal work by O'Kelly, which introduced the single allocation p-hub median problems using a model based on quadratic integer programming (O'Kelly, 1986a, 1986b, 1987). Later, a multiple allocation model based on linear integer programming was developed by Campbell (1992). The intermodal hub location problem was first introduced by Arnold et al., who proposed a mixed integer programming (MIP) model that minimized the fixed costs for the opening of IMTs and variable costs for unimodal and intermodal transportation (Arnold et al., 2001, 2004). These studies established the foundation for further research in intermodal terminal location-allocation problems which has grown significantly in the last three decades.

Ishfaq et al. (2011) developed a multiple allocation p-hub median model for road-rail intermodal transportation network which considered different fixed costs for opening new hubs depending on their location and modal connectivity along with timely service constraints. A tabu search meta-heuristic was used to obtain solutions for large-sized problems. Meng et al. (2011) presented an intermodal hub and spoke network design problem which considered multi-type containers and multiple stakeholders: the network planner, carriers, hub operators, and intermodal operators and was solved using a hybrid genetic algorithm. Alumur et al. (2012) developed a mixed-integer linear programming (MILP) model that jointly considered transportation costs and travel times and was solved using a heuristic.

Sorensen et al. (2013) adapted the original model presented in Arnold et al. (2001) to develop a bi-objective problem considering different stakeholders. The model used two objective functions which minimized transportation cost from the network user's perspective and location cost from the terminal operator's perspective. Serper et al. (2016) developed a MIP model which designed an intermodal hub network and considered different types of vehicles available. Their model also determined how many vehicles of a type should be purchased and between which hub pairs to operate them. Teye et al. (2017) formulated a non-linear mixed-integer programming model that solves the facility location problem but also gives the shippers a choice of whether to use an IMT or not.

Ghane-Ezabadi et al. (2016) developed a path-based integer programming model that uses composite variables to integrate tactical and operational decisions with the strategic decisions of locating IMTs. The problem is solved using a decomposition approach where the master problem solves for hub locations and the subproblem finds the optimal load routes and chooses transportation modes to evaluate hub locations. Abbasi et al. (2019) applied a hybrid approach combining Population Based Simulated Annealing (PBSA) and an exact method to both a deterministic model and a robust optimization model for uncertainties in costs, capacities of IMTs, and uncertainties in transportation costs.

To this point, all the research that has been discussed assumes a single planning period. Including multiple periods planning has been getting significant attention in recent times as it is more realistic. The first work in multi-period (or dynamic) hub location was proposed by Campbell (1990) that involved a continuous variable approximation model for hub location with demand growing over time. Contreras et al. (2011) presented a dynamic uncapacitated hub location problem where total cost was minimized over the planning horizon and the hubs could be opened or closed in a time period. Alumur et al. (2015) proposed a multi-period MILP model with both single and multiple allocations and where capacities could be expanded gradually over time. According to Alumur et al. (2015), they were the first to consider hub capacities in a multi-period model.

Finally, some research has considered stochasticity in parameters like transportation costs, demands, and capacities. Contreras et al. (2011) proposed a stochastic model for hub locations with uncertain demands and transportation costs. Fotuhi et al. (2015) proposed a stochastic model for competitive IMT location problems with uncertain demands. In our study, we consider the demands to be forecasted beforehand and thus model is deterministic. We assume that the IMTs can hold inventory over a few periods. A similar approach was used by Bhattacharya et al. (2014) but not in a multi-period setting.

**Table 2.1 Comparison between different relevant studies based on literature review.**

| Reference | Objective | Modeling approach | Multi-Period | Budget constraint | Inventory at IMTs | Volume Considered | Uncertainty in Parameters |
|---|---|---|---|---|---|---|---|
| Ishfaq et al. 2011 | Cost minimization | Multiple allocation p-hub median | x | x | x | x | x |
| Contreras et al. 2011a | Cost minimization | Mixed integer programming | ✓ | x | x | x | x |
| Contreras et al. 2011b | Cost minimization | Mixed integer programming | x | x | x | x | ✓ |
| Alumur et al. 2012 | Cost minimization | Mixed integer programming | x | x | x | x | x |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| Sorenson et al. 2013 | Cost minimization | Bi-objective mixed integer programming | x | x | x | x | x |
| Bhattacharya et al. 2014 | Cost minimization | Mixed integer programming | ✓ | x | ✓ | x | x |
| Fotuhi et al. 2015 | -- | Mixed integer non-linear programming | x | x | x | x | ✓ |
| Alumur et al. 2016 | Cost minimization | Mixed integer programming | ✓ | x | x | x | x |
| Ghane-Ezabadi et al. 2016 | Cost minimization | Integer programming | x | x | x | x | x |
| Abbassi et al. 2019 | Cost minimization | Mixed integer programming | x | x | x | x | ✓ |
| Current Research | Cost minimization | Mixed integer programming | ✓ | ✓ | ✓ | ✓ | x |

The key contribution of this work is in the expanded nature and scope of the capacitated multi-period freight flow model. In addition to traditional factors like budget, demand, and mode choices, the model developed includes multiple product types and the opportunity for inventory to be held at the IMTs. By using volume as the basis for defining freight flow, the model allows decision-makers to explore more options for designing the network including consolidating loads of different products. This is particularly interesting since the model allows customers to order specific products from a specific shipper or have the order filled by any shipper with supply capacity. By including these types of features, the model can be used to explore issues like the impact that the amount of space in an IMT dedicated to holding inventory, and/or how long that inventory is held, has on network efficiency. Hence, this model is fundamentally different from existing models in the literature on IMTLP and can be used to provide decision-makers more insight into designing IMT networks to support vertical and horizontal collaboration.

## 2.3 Models for less than truckload carrier collaboration

The following literature review focuses on horizontal collaboration between carriers. Readers are referred to the work of Barratt (2004) and Chen et al. (2017) for a review of vertical collaboration.

Carrier collaboration can be achieved in two ways: by sharing the received jobs or by sharing the vehicle capacity (Verdonck et al., 2013). Nadarajah (2008) introduced a two-stage solution methodology for LTL carrier collaboration (LTLCC) where the carriers share their vehicle capacity at the entrance of the city as well as at the transshipment facilities. He used a local search heuristic to solve the model. His numerical results showed that collaborating at the entrance of the city reduced the total distance traveled by 7 to 15% while the intra-city collaboration further reduced the distance by 3 to 15%. Nadarajah and Bookbinder (2013) continued this basic idea with a three-phase approach. The first phase was to address the entry point collaboration, the second phase was to locate facilities and the third phase was to build collaborative routes using a greedy heuristic. Numerical experiments using this approach indicated that collaboration reduces the total distance by 12% and travel time by 15%. Hernández and Peeta (2014) addressed a version of the LTLCC problem in which a single carrier seeks to collaborate with other carriers to increase capacity utilization. They solved the cost minimization problem using a branch-and-cut algorithm and the results showed that the LTLCC increases the vehicle capacity utilization. Houghtalen et al. (2011) proposed a profit maximization problem for carrier collaboration by sharing the vehicle capacity. They assumed that the vehicle capacity is limited, and they modeled the behavior of individual carriers based on two approaches: limited control and strict control. The former assumed that the carrier's decisions are restricted on a particular route, whereas, the latter assumed that a single carrier has full control over decision making. The authors found that limited control guaranteed the collaborative feasibility while the other does not. Sprenger and Monch (2012) considered a problem in the food industry where several manufacturers share the vehicle capacity at the main manufacturing center or intermediate distribution centers. These manufacturers have overlapping customers or complementary products and the aim was to reduce the delivery cost and improve the on-time delivery performance. They decomposed the problem into two phases. The first phase splits up the entire problem into vehicle routing subproblems and the second phase solves these subproblems using greedy heuristic and ant colony optimization. Dai and Chen (2012) developed a mathematical model to determine the optimal vehicle routes for pickup and delivery when shippers/carriers collaborate to minimize the total transportation cost for LTL carriers. They solved their model using Lagrangian relaxation. Voruganti et al. (2011) compared two mechanisms for collaboration: partial and complete collaboration. In partial collaboration, each carrier shares vehicle capacity to maximize its profit, whereas, in complete collaboration, all carriers work jointly to maximize the profit of the alliance. They found that partial collaboration is as effective as complete collaboration in most cases. Hernández and Peeta (2011) developed a binary, multi-commodity minimum cost flow model to address the time-dependent, centralized multiple carrier collaboration problems and solved them using branch and cut algorithm. They tested the performance of the model under various rate-setting strategies and found that the capacity utilization is increased for member carriers under a volume-oriented rate-setting strategy.

Researchers have addressed carrier collaboration by job sharing either with centralized planning or decentralized planning. Dai and Chen (2011) proposed a multi-agent, auction-based framework for the LTLCC problem using decentralized planning. The objective function was to maximize the total profit of the carrier. In their problem, the carriers act as auctioneer when they want to outsource a job and they act as a bidder when they want to acquire a job. Dai et al. (2014) proposed a multi-round price-setting approach based on combinatorial auction to solve the LTLCC with decentralized planning. Hernandez et al. (2011) proposed a deterministic dynamic carrier collaboration problem from the perspective of a single carrier to analyze the potential benefit of carrier collaboration for small to medium-sized LTL carriers. A multi-commodity minimum cost flow model for the proposed problem was developed and solved using a branch-and-cut algorithm. Another decentralized planning approach was presented by Berger and Bierwirth (2010) in which the objective was to maximize the profit of the alliance without decreasing the individual profit of the carriers. They compared the results of decentralized planning to that of non-collaboration and centralized planning. They found that centralized planning has more potential to improve network profit than decentralized planning. Two algorithms were developed to address the decentralized planning; however, the authors did not mention how the problem was solved under centralized planning. Li et al. (2016) investigated a decentralized planning problem where each carrier in the alliance tries to maximize the profit by collaborating with other carriers. They developed a profit maximization model and an adaptive large neighborhood search methodology to solve the problem. They approached the problem from the perspective of a single carrier and assumed that each carrier can have reserved jobs and selective jobs. The reserved jobs must be served by the same carrier and selective jobs can be served by other carriers in the alliance or remained unserved.

Centralized planning is another key area researchers are interested in. Krajewska et al. (2008) discussed a carrier collaboration problem where carriers share all received jobs. They assumed that each carrier has only one vehicle to serve all jobs and the profit allocation to the carriers was done using cooperative game theory. They did not provide a mathematical model for the problem; instead, they solved the problem using an adaptive large neighborhood search heuristic. Gansterer et al. (2017) addressed an LTLCC problem with pickup and delivery under centralized planning as a traveling salesman problem. They used the concept of Hamiltonian tour formulation as suggested by Lu and Dessouky (2004) where the destination depot of one vehicle is the departure depot of the next vehicle. They also assumed that there is only one vehicle at each carrier depot. They solved a small network that consists of 3 carriers and 3 jobs for each carrier by using bender's decomposition, column generation, and branch-and-cut. Bender's decomposition was found to be superior to both branch-and-cut and column generation. Vaziri et al. (2019) addressed the many-to-one pickup and delivery problem where a fleet of heterogeneous vehicles from the same carrier start and end their trips at a single depot. They assumed that the central authority collects all jobs from the suppliers and each vehicle is having independent profit centers. In their study, the reserved jobs must be served, and the selective jobs can remain unserved if they are not profitable. They developed a mathematical model and a solution methodology based on a genetic algorithm. Adenso (2014) studied the effect of the size of the coalition when full truckload carriers collaborate in centralized planning. They found cost savings to decrease as the size of the coalition increases. Buijs et al. (2016) developed a generalized pickup and delivery model to address the collaborative planning of two autonomous business units of a Dutch logistic service provider, Fritom. Based on their experimental results, they proposed methods to improve Fritom's existing collaborative transport planning process. Lin (2008) introduced a collaborative model with pickup and delivery time windows based on the daily operations of a local courier service of a multinational logistics company. His model results indicated that the cooperative strategy saves up to 20% of the travel cost.

All of the aforementioned studies formulated the LTLCC problem as a vehicle routing problem (VRP). However, some studies have formulated it as an arc routing problem (ARP). For example, Fernandez et al. (2016) addressed the uncapacitated ARP with carrier collaboration, but they did not consider real-world constraints and practices such as time window and pickup and delivery in a single-vehicle route. Recent studies involving carrier collaboration have focused on environmental benefits. For example, Montoya et al. (2016) discussed the impact of the carrier collaboration on congestion and emissions in an urban area. Perez et al. (2015) reported that carrier collaboration can reduce both transportation costs and greenhouse gas emissions. Sanchez et al. (2016) argued that pooling resources in VRP reduce the carbon footprint and economic cost. They developed a mathematical model for VRP with time window constraints and with carbon footprint constraints. Soysal et al. (2018) analyzed the environmental benefits of horizontal collaboration that are related to $CO_2$ emission in the inventory routing problem and showed that the total emission benefits vary between 8 and 33%.

From the above review, it can be seen that horizontal collaboration between carriers, either centralized or decentralized, provides significant benefits in terms of cost or distance traveled. However, the centralized planning approach has been shown to provide more benefits than the decentralized planning approach (Berger & Bierwirth, 2010). Also, the above review reveals a gap in the current body of work. That is, the potential benefits of allowing carriers to retain some of the jobs under the centralized collaborative planning approach are not addressed. The job distribution under this scenario is a major challenge in carrier collaboration as reported by Cleophas et al. (2019). In addition, the analysis of the complex systems that consist of multiple depots, multiple vehicles at each carrier depot, etc. is reported as a gap in the current literature of centralized carrier collaboration (Gansterer & Hartl, 2017). While the operational constraints such as time window and vehicle capacity have been addressed in the centralized carrier collaboration literature, the restriction on trucks' service hours and mixed pickup and delivery in a single route have not been addressed. It is important that these constraints are also considered in the model to evaluate the actual benefits of carrier collaboration. Additionally, no study to date has examined the variation of cost savings under various collaboration scenarios. This study addresses the aforementioned shortcomings.

# CHAPTER 3

## A Two-stage Model for Intermodal Transportation

Intermodal transportation can allow for efficient freight shipping at reduced costs due to economies of scale, consolidation, and inventory. The location of IMTs, number of IMTs to be opened, and space allocation for inventory at IMTs, are long term decisions and strategic. The planning horizon for IMTLP is typically more than 25-30 years. The multi-period approach allows us to account for the dynamic nature of input parameters like cost and capacities and allow the use of inventory at IMTs. Intermodal transportation however is not a desirable option for short distance shipping such as pre-hauls and end-hauls from consolidation centers which is usually done by LTL carriers. The shorter distance freight shipping doesn't allow to take advantage of discounted shipping costs over intermodal links, and the costs for freight handling and other operational costs at IMTs make it a less desirable option. Whereas, collaboration among LTL carriers by sharing their pickup and delivery jobs can improve the transportation efficiency of short distance shipping. Thus, the total distance traveled, total transportation cost and the number of empty backhauls can be reduced. These job-sharing decisions are short-term/operational and should be modeled using a single period approach.

**Figure 3.1** shows a flowchart explaining the overall framework of both strategic and operational decision-making processes. The planner receives supply availability and demand information from customers over the planning horizon, which is composed of many time periods. Corresponding to their freight zones, demand and supply availability data is aggregated at the consolidation centers for each period. Strategic decision making involves finding the optimal modes/methods to ship a product from the shipper's consolidation center to the consignee's consolidation center (intermodal shipping or direct shipping). The inputs required include a budget for the entire planning horizon, potential IMT locations, mode frequencies, inventory capacities, and threshold capacities for IMTs for each period. The output includes the location of IMTs, the time period when an IMT is opened, and for each period: inventory and throughput at IMTs, freight flows between consolidation centers, mode choices on IMT links. The freight flows once decided for each period, determines the freight flows between customers and consolidation centers, which represents jobs for the second stage/operational decision making.

The operational decision making should be executed every period for the corresponding jobs. Multiple trucking companies (carriers) receive these jobs and they independently serve most cost-effectively (i.e., they seek the least-cost routes). When carriers share a portion or all of their jobs with other carriers, the total distance/cost of transportation to serve these jobs can be reduced. Operational decision making involves finding the optimal allocation of shared jobs to the carriers by finding the optimal vehicle routes to serve the jobs. A centralized collaborative planning approach is adopted with a key modification. In traditional centralized collaborative planning, the carriers release all of their jobs to a common pool and a central authority optimally allocates the pooled jobs (released jobs) among the alliance members. In this study, the carriers are allowed to retain some jobs to serve using their vehicles and release rest to the common pool for sharing. The inputs required include pickup and delivery locations of each job (these include the location of consolidation centers and customers' location), carrier's depots from where the carriers start and end their trip, the quantity of freight to be picked up and delivered, time window at each pickup and delivery location, vehicle capacity, time and cost (distance) of transportation between any two locations in the network, maximum allowable distance in a single vehicle route, retained jobs and pooled jobs of each carrier. The output includes for each carrier: the number of jobs to be served, information on the jobs to be served (pickup location, delivery location, quantity and time of pickup and delivery), and the vehicle routes to serve these jobs.

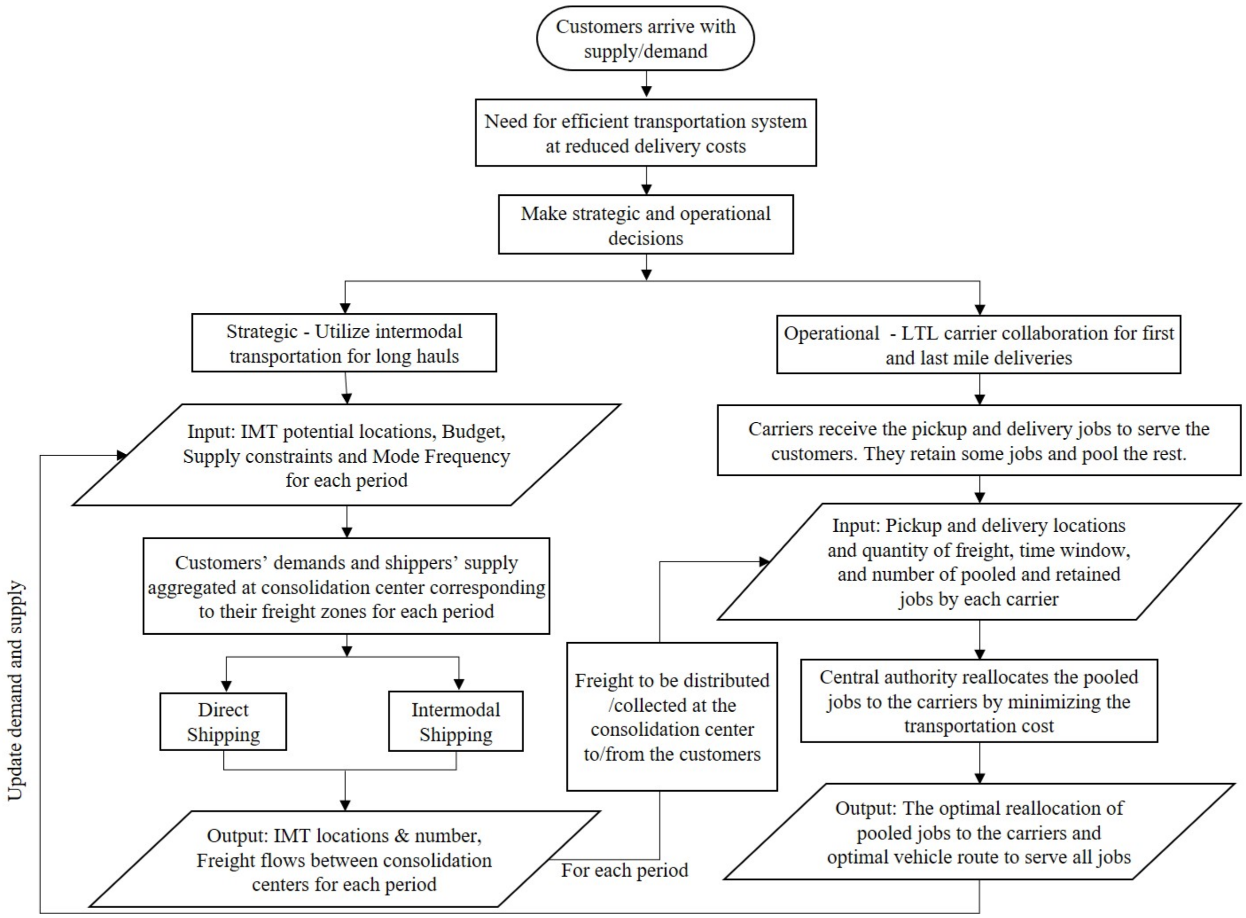



**Figure 3.1 Overall framework of the two-stage model**

The strategic model is long term, and the demands realized can differ from the demand forecasts. This can be countered by executing the strategic model after a fixed number of periods (one cycle) as deemed necessary by the decision makers. The operational model is executed on a short term basis and thus has the information of actual demands. The demands realized information available from the operational model can be used to develop better forecasts for demands for the next cycle to be used for the strategic model. This would allow the decision makers to make necessary strategic changes to tackle the uncertainty in demand. **Figure 3.2** illustrates this rolling horizon decision making over a planning horizon of 12 periods. Model-1 (first stage model) is executed using the forecasted demands and supplies for the entire planning horizon at 'Period 0', which generates the forecasted jobs for the Model-2 (second stage model) for all 12 periods. Model-2 is then executed for the first cycle (Period 0 to Period 4) to determine the freight distributions to end customers. This process can be repeated after every 4 periods using the updated demand forecasts for the remaining period. This gives the decision makers a chance to make any necessary changes to the planning against uncertainty in demand.

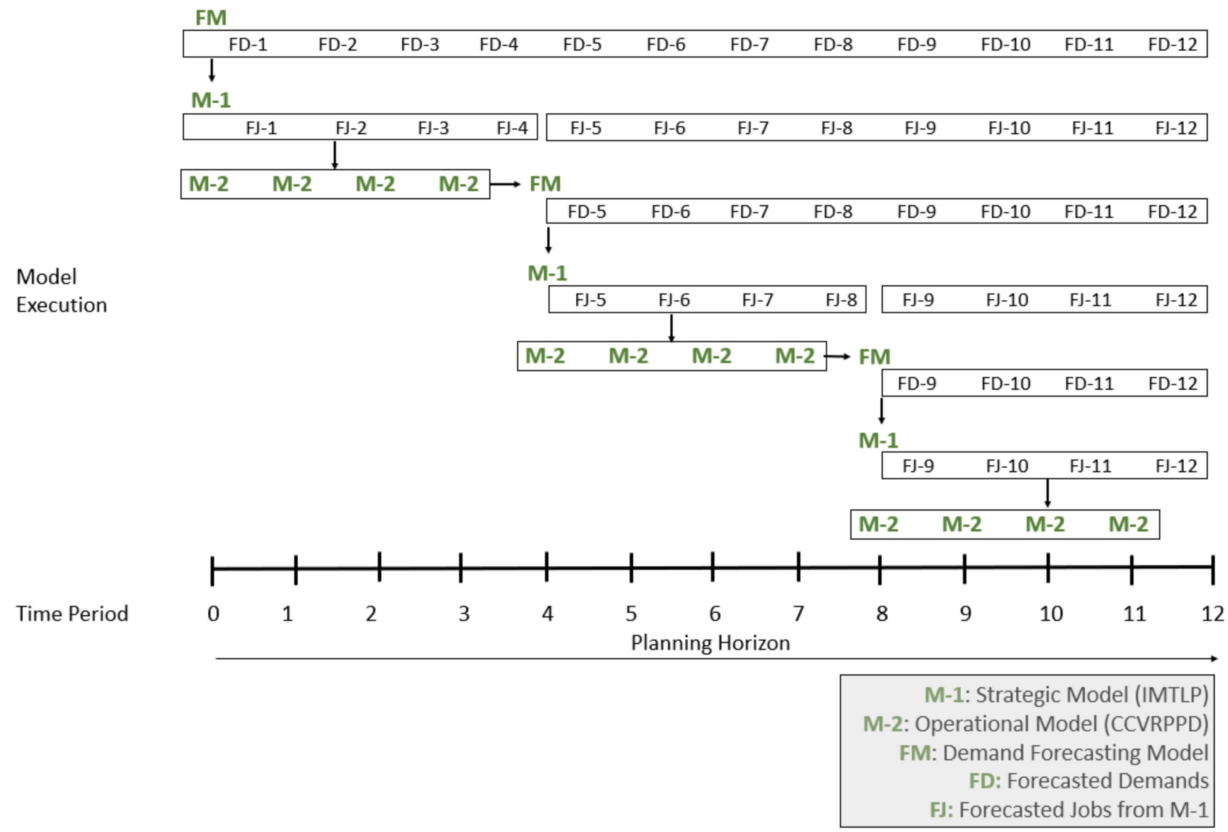



**Figure 3.2 Rolling horizon decision making**

It is thus evident that the two above-mentioned processes (strategic and operational decision making) are physically separated in the real world. Therefore, this problem can be modeled as a two-stage model. The first stage is strategic, multi-period, and deals with the efficient transfer of freight between different modes at intermodal terminals (IMT). The second stage is operational, a single period, and deals with collaboration among LTL carriers to improve the efficiency of regional truck transportation. Chapters 4 and 5 explain the IMTLP and CCVRPPD models, respectively.

**Figure 3.3** illustrates how these two models can be integrated into a two-stage model by using a small network. Node 3 represents the consolidation center (shipper/consignee for the strategic model) where the freight should be consolidated by the carriers for long-haul shipping and/or regional distribution. The strategic model (IMTLP) decides the freight flows between the consolidation centers while finding the optimal number and location of intermodal terminals and mode choice on intermodal routes. That means the details of the products that should be picked up from the consolidation center and delivered to end customers and picked up from end customers and delivered to the consolidation center. Each pickup and delivery pair is considered a job. Multiple carriers receive these jobs to serve the end customers.

In this illustrative example, there are two carriers, 1 and 2. Before the carriers collaborate, the vehicles of each carrier start from its carrier depot to fulfill the jobs that they have received. **Figure 3.3a** shows the vehicle routes to serve the jobs when carriers 1 and 2 are not collaborating. When the carriers collaborate, they exchange jobs between them in such a way that the total cost (or distance) of transportation is minimized. The operational model (CCVRPPD) finds the optimal routes and job allocation under collaborative planning. **Figure 3.3b** shows the vehicle routes to serve the jobs when carriers 1 and 2 collaborate. With collaboration, the routes could be drastically different as shown in **Figure 3.3b** since the carriers are serving a different set of jobs.

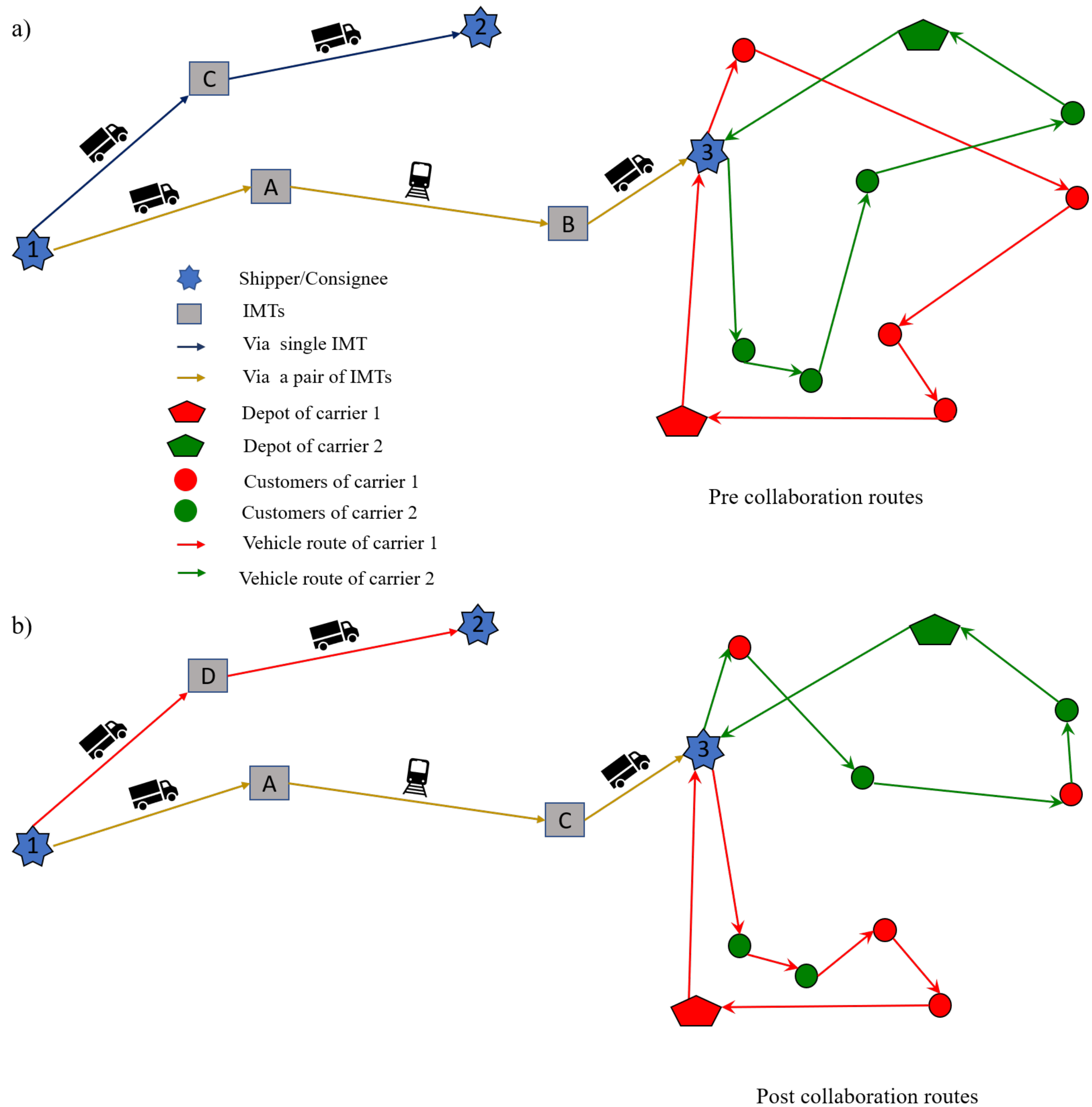



**Figure 3.3 Two-stage model with IMT locations, mode choice on intermodal routes and a) pre collaboration vehicle routes b) post collaboration vehicle routes.**

# CHAPTER 4

## Strategic Model for Locating Intermodal Terminals

A MILP based mathematical model is proposed for the IMTLP. This chapter provides the problem description, mathematical formulation, and results from the application of the model to the state of South Carolina using public data sets.

### 4.1 Problem description

This research focuses on locating IMTs from a set of candidate locations to minimize the total relevant network cost which includes the fixed cost to open an IMT, the fixed cost of an intermodal link, transportation costs, loading/unloading costs, and inventory holding costs. Pre-haul and end-haul, the short distance freight is carried from shippers to the IMT and from the IMT to the consignee, are only considered relative to their truck capacities.

It is assumed that freight flows are limited to three types: (1) direct shipping from shipper to customer, (2) intermodal shipping from shipper to the customer via a pair of IMTs, and (3) shipper to the customer through a single IMT. The sum of the latter two flow types together is considered intermodal shipping. This solution to this model defines a new network and does not consider the existing terminals for capacity expansion. The network is assumed to be completely connected and capacitated. The hub nodes are potential candidates for being opened in any time period and, once opened, they remain open for all subsequent time periods. The non-hub nodes can either be a shipper or consignees or both.

This model considers product types, product volumes, mode choices, mode capacities, and allows restrictions on the number of trips available between any two nodes. The IMTs have a throughput capacity (freight handling capacity), which is the sum of inbound and outbound flows. It is assumed that there is a known budget for opening IMTs for the entire planning horizon that cannot be exceeded. The IMTs can hold inventory and unloading, holding, and loading costs are incurred depending on the product type. The consignees can demand a specific product type from a specific shipper, or they can simply have their demand for that product satisfied from any shipper. Henceforth, the former will be referred to as "specific demand" and the latter "free demand."

The remaining key assumptions are: (i) The transfer of goods between the non-hub nodes and hub-nodes is done only by truck, (ii) at most two IMTs may be used for freight flow through the intermodal network, (iii) there is a capacity on the amount of inventory that can be held at each IMT.

To address the design and control of this intermodal network, a multiple-allocation capacitated mixed-integer linear programming model is proposed. The decision variables determine: (i) the location of the intermodal terminals, (ii) freight routing, (iii) the transportation mode between IMTs, and (iv) the amount of inventory to hold at the IMTs. The objective function is to minimize the total cost of the network that includes the fixed cost of opening new IMTs, transportation costs, loading and unloading costs at IMTs, and inventory holding costs at the IMTs for a specified planning horizon. The planning horizon is the entire time period for which strategic planning is done and can be further divided into shorter periods of equal or unequal duration.

## 4.2 Mathematical formulation

This section describes the mathematical programming model and notation.

**Notation:**

Sets and parameters

| | |
|---|---|
| $N$ | Set of all nodes |
| $H$ | Set of candidate hubs, $H \subset N$ |
| $P$ | Set of products |
| $M$ | Set of transportation modes |
| $T$ | Set of time periods |
| $F_i$ | fixed cost for opening an IMT $i \in H$ |
| $f_{ijm}^t$ | fixed cost for operating on a terminal link using mode $m \in M$ between IMTs $i \in H$ and $j \in H$ in period $t \in T$ |
| $CI_{ijmp}^t$ | per unit transportation cost for product $p \in P$ from IMT $i \in H$ to IMT $j \in H$ using mode $m \in M$ in period $t \in T$ |
| $CP_{kip}^t$ | per unit drayage cost for product $p \in P$ from shipper $k \in N$ to IMT $i \in H$ using road transport in period $t \in T$ |
| $CE_{jgp}^t$ | per unit drayage cost for product $p \in P$ from IMT $j \in H$ to receiver $g \in N$ using road transport in period $t \in T$ |
| $CU_{ip}^t$ | per unit unloading cost for product $p \in P$ at IMT $i \in H$ in period $t \in T$ |
| $CL_{ip}^t$ | per unit loading cost for product $p \in P$ at IMT $i \in H$ in period $t \in T$ |
| $CH_{ip}^t$ | per unit holding cost for product $p \in P$ at IMT $i \in H$ in period $t \in T$ |
| $CD_{kgp}^t$ | per unit direct shipping cost for product $p \in P$ between shipper $k \in N$ and receiver $g \in N$ in period $t \in T$ |
| $D_{gkp}^t$ | specific demand for product $p \in P$ belonging to shipper $k \in N$ at receiver $g \in N$ in period $t \in T$ |
| $DT_{gp}^t$ | total demand for product $p \in P$ at receiver $g \in N$ in period $t \in T$ |
| $S_{kp}^t$ | number of units of product $p \in P$ available at shipper $k \in N$ in period $t \in T$ |
| $VP_p$ | per unit volume of product $p \in P$ |
| $VM_m$ | volume capacity of a mode $m \in M$ |
| $VT$ | volume capacity of a pre-haul/end-haul truck |
| $TI_{ijm}^t$ | maximum number of trips available between IMTs $i \in H$ and $j \in H$ for a mode $m \in M$ in period $t \in T$ |
| $TP_{ki}^t$ | maximum number of pre-haul trips available between shipper $k \in N$ and IMT $i \in H$ in period $t \in T$ |
| $TE_{jg}^t$ | maximum number of end-haul trips available between IMT $j \in H$ and receiver $g \in N$ in period $t \in T$ |
| $TD_{kg}^t$ | maximum number of direct shipping trips available between shipper $k \in N$ and receiver $g \in N$ in period $t \in T$ |
| $C_i^t$ | material handling capacity of IMT $i \in H$ in period $t \in T$ |
| $HC_i^t$ | inventory holding capacity of IMT $i \in H$ in period $t \in T$ |
| $B$ | budget for opening IMTs for the entire planning horizon |

Decision variables

$$\xi_i = \begin{cases} 1, & \textit{if} \text{ IMT } i \in H \text{ is open} \\ 0, & \textit{otherwise} \end{cases}$$

$$z_{ijm}^t = \begin{cases} 1, & \textit{if} \text{ mode m} \in \text{M is used between IMTs } i \in H \text{ and } j \in H \text{ in period } t \in T \\ 0, & \textit{otherwise} \end{cases}$$

$$y_i^t = \begin{cases} 1, & \textit{if} \text{ IMT } i \in H \text{ is open in period } t \in T \\ 0, & \textit{otherwise} \end{cases}$$

$x_{ijmkp}^t$ number of units of product $p \in P$ belonging to shipper $k \in N$ shipped from IMT $i \in H$ to IMT $j \in H$ using road transport in period $t \in T$

$q_{kip}^t$ number of units of product $p \in P$ shipped from shipper $k \in N$ to IMT $i \in H$ using road transport in period $t \in T$

$r_{jgkp}^t$ number of units of product $p \in P$ belonging to shipper $k \in N$ shipped from IMT $j \in H$ to customer $g \in N$ using road transport in period $t \in T$

$w_{kgp}^t$ number of units of product $p \in P$ direct shipped from shipper $k \in N$ to receiver $g \in N$ in period $t \in T$

$u_{ikp}^t$ number of units of product $p \in P$ belonging to shipper $k \in N$ unloaded at IMT $i \in H$ in period $t \in T$

$l_{ikp}^t$ number of units of product $p \in P$ belonging to shipper $k \in N$ loaded at IMT $i \in H$ in period $t \in T$

$h_{ikp}^t$ number of units of commodity $p \in P$ belonging to shipper $k \in N$ held by IMT $i \in H$ in period $t \in T$

**Mathematical Formulation:**

The proposed Mixed Integer Linear Programming model is presented below,

Minimize,

$$\begin{aligned}
&\sum_{i \epsilon H} F_i \xi_i + \sum_{i \epsilon H} \sum_{j \epsilon H} \sum_{m \epsilon M} \sum_{t \epsilon T} f_{ijm}^t z_{ijm}^t + \sum_{i \epsilon H} \sum_{j \epsilon H} \sum_{m \epsilon M} \sum_{k \epsilon N} \sum_{p \epsilon P} \sum_{t \epsilon T} CI_{ijmp}^t x_{ijmkp}^t \\
&+ \sum_{k \epsilon N} \sum_{i \epsilon H} \sum_{p \epsilon P} \sum_{t \epsilon T} CP_{kip}^t q_{kip}^t + \sum_{j \epsilon H} \sum_{g \epsilon N} \sum_{k \epsilon N} \sum_{p \epsilon P} \sum_{t \epsilon T} CE_{jgp}^t r_{jgkp}^t + \sum_{i \epsilon H} \sum_{k \epsilon N} \sum_{p \epsilon P} \sum_{t \epsilon T} CU_{ip}^t u_{ikp}^t \\
&+ \sum_{i \epsilon H} \sum_{k \epsilon N} \sum_{p \epsilon P} \sum_{t \epsilon T} CL_{ip}^t l_{ikp}^t + \sum_{i \epsilon H} \sum_{k \epsilon N} \sum_{p \epsilon P} \sum_{t \epsilon T} CH_{ip}^t h_{ikp}^t \\
&+ \sum_{k \epsilon H} \sum_{g \epsilon N} \sum_{p \epsilon P} \sum_{t \epsilon T} CD_{kgp}^t w_{kgp}^t
\end{aligned} \qquad (1)$$

Subject to,

$$\sum_{\substack{j\in N,\\ j\neq i}}\sum_{m\in M} x^t_{jimkp} + \sum_{k\in N} q^t_{kip} + l^t_{ikp} = \sum_{m\in M}\sum_{j\in H} x^t_{ijmkp} + \sum_{\substack{j\in H,\\ j\neq i}}\sum_{g\in N} r^t_{jgkp} + u^t_{ikp} \quad \forall i \in H, k \in N, p \in P, t \in T \tag{2}$$

$$h^t_{ikp} = h^{t-1}_{ikp} + u^t_{ikp} - l^t_{ikp} \quad \forall i \in H, k \in N, p \in P, t \in T \tag{3}$$

$$w^t_{kgp} + \sum_{j\in H} r^t_{jgkp} \geq D^t_{gkp} \quad \forall g,k \in N{:}\, g \neq k, p \in P, t \in T \tag{4}$$

$$\sum_{k\in N} w^t_{kgp} + \sum_{k\in N}\sum_{j\in H} r^t_{jgkp} \geq DT^t_{gp} \quad \forall g \in N, p \in P, t \in T \tag{5}$$

$$\sum_{i\in H} q^t_{kip} + \sum_{\substack{g\in N,\\ g\neq k}} w^t_{kgp} \leq S^t_{kp} \quad \forall k \in N, p \in P, t \in T \tag{6}$$

$$\sum_{k\in N}\sum_{p\in P} x^t_{ijmkp} VP_p \leq TI^t_{ijm} VM_m z^t_{ijm} \quad \forall i,j \in H{:}\, i \neq j, m \in M, t \in T \tag{7}$$

$$\sum_{p\in P} q^t_{kip} VP_p \leq TP^t_{ki} VT y^t_i \quad \forall k \in N, i \in H, t \in T \tag{8}$$

$$\sum_{k\in N}\sum_{p\in P} r^t_{jgkp} VP_p \leq TE^t_{jg} VT y^t_j \quad \forall g \in N, j \in H, t \in T \tag{9}$$

$$\sum_{p\in P} w^t_{kgp} VP_p \leq TD^t_{kg} VT \quad \forall g \in N, j \in H, t \in T \tag{10}$$

$$\sum_{\substack{j\in H,\\ j\neq i}}\sum_{m\in M}\sum_{k\in N}\sum_{p\in P} x^t_{ijmkp} + \sum_{\substack{j\in H,\\ j\neq i}}\sum_{m\in M}\sum_{k\in N}\sum_{p\in P} x^t_{jimkp} \leq C^t_i \quad \forall i \in H, t \in T \tag{11}$$

$$\sum_{i\in H} F_i \xi_i \leq B \tag{12}$$

$$\sum_{k\in N}\sum_{p\in P} h^t_{ikp} \leq HC^t_i \quad \forall i \in H, t \in T \tag{13}$$

$$z^t_{ijm} \leq y^t_i \quad \forall i,j \in H{:}\, i \neq j, m \in M, t \in T \tag{14}$$

$$z^t_{ijm} \leq y^t_j \quad \forall i,j \in H{:}\, i \neq j, m \in M, t \in T \tag{15}$$

$$y^t_i \geq y^{t-1}_i \quad \forall i \in H \tag{16}$$

$$M\xi_i \geq \sum_{t\in T} y^t_i \quad \forall i \in H \tag{17}$$

$$z^t_{ijm}, y^t_i, \xi_i \in \{0,1\} \quad \forall i,j \in H{:}\, i \neq j, m \in M, t \in T \tag{18}$$

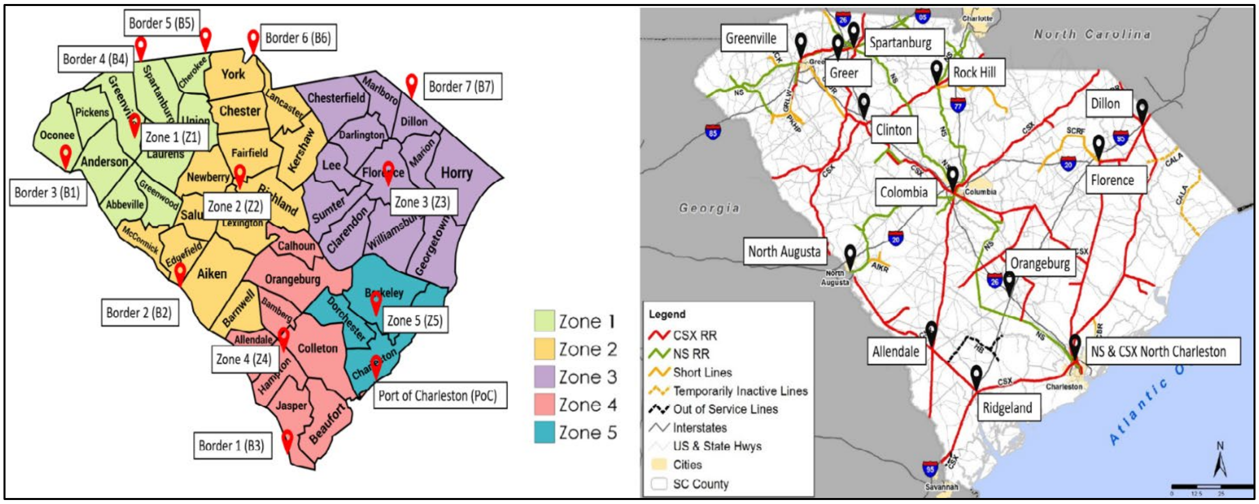
$$q^t_{kip}, x^t_{ijmkp}, r^t_{jgkp}, w^t_{kgp}, u^t_{ik}, l^t_{ik}, h^t_{ik} \geq 0 \text{ and } Int \quad \forall k,g \in N{:}\, k \neq g, i,j \in H{:}\, i \neq j, m \in M, p \in P, t \in T \tag{19}$$

The objective function (1) minimizes the total relevant network cost which includes the fixed costs of opening an IMT and using an intermodal link; and the variable costs of shipping between IMTs, pre-hauls, end-hauls, unloading/loading/holding at IMTs, and direct shipping. Constraints (2) are the flow balance constraints at IMTs. They also track the number of loaded and unloaded units of a product. Constraints (3) are the multi-period inventory constraints that also balance material flow at an IMT across periods. Constraints (4) ensure that a consignee has its demand for a specific product type from a specific shipper met. (This is called the specific demand.). Constraints (5) ensure that a consignee meets its net demand (sum of specific and free demand). Constraints (6) enforces capacity on a shipper so only the available amount of freight can be shipped. Constraints (7-10) ensure that a mode cannot exceed the net available volume. Constraints (11) are the throughput constraints at an IMT and consider both the inbound and outbound flows. Constraints (12) enforces the limited budget available to open intermodal terminals. Constraints (13) limit the inventory being held at each IMT in each period to less than its storage capacity. Constraints (14, 15) ensure that an intermodal link is used only if the IMTs connected by the link are open. Constraints (16) ensure that an IMT stays open for all subsequent periods after it is opened. Constraints (17) assign the one-time fixed cost required to open an IMT if being utilized in any time period. Here M is a number greater than or equal to the total number of time periods. The decision variable '$y_i^t$' keeps track of an IMT's status (i.e., open or closed) in each time period. The fixed cost to open an IMT is incurred only once and this is modeled using the binary decision variable '$\xi_i$'. Constraints (18, 19) define the variable types.

## 4.3 Results and discussion

### 4.3.1 South Carolina case study

The model is now used in a case study based on South Carolina data. The State is divided into five regional zones that are developed by utilizing regional map divisions, and the FAF zones. There are 26 total nodes in the case study network with 13 representing the freight supply and demands as illustrated in **Figure 4.1a.** These include six consolidation centers, one in each of the five regional zones, another at the Port of Charleston (PoC) considering the significance of freight flow through PoC, and seven locations where the major interstate highways cross the state border. The other 13 nodes are the potential IMT locations and are shown in **Figure 4.1b.** They are located at major road and rail intersections across the State and existing intermodal facilities (i.e., Inland Port of Greer, Inland Port of Dillon, and the Norfolk Southern and CSX intermodal facility in North Charleston). The case study uses data from 2017 and a planning horizon of 12 months that is divided into 12, one-month periods.




**(a)** **(b)**

**Figure 4.1 (a)The map shows 13 customer nodes, the five zones, and (b) the map shows the 13 potential IMT locations (Source 1(b): South Carolina Statewide Freight Plan, 2017, SCDOT, https://www.scdot.org/Multimodal/pdf/SC_MTP_Freight_Plan_FINAL.pdf )**

In the model, consolidation centers are assumed to be located at single points in each region. These are determined by minimizing the total distance between the consolidation center location and the mean population centers of each county in the zone (Centers of Population, 2010). The FAF4 Origin-Destination Data (FAF[4], BTS & FHWA) for South Carolina FAF zones (**Figure 4.1a**) was used for this case study. The FAF data was disaggregated to the five-zone level using two disaggregation factors: (i) commodity-specific quarterly industry employment data for freight origins in 2017 and, (ii) annual estimates of the resident population for freight destinations in 2017 - as proportional weights to the specific zones (Opie et al., 2009). The Standard Classification of Transported Goods (SCTG) - North American Industry Classification System (NAICS) cross-reference (Anderson et al., 2013) was used to generate the employment data for the five zones specific to the commodities. The employment and population datasets for the 12 time periods were then approximated using linear regression.

The case study considers seven product types based on the highest tonnage of freight moved for interstate flows, both imports, and exports. Three mode choices are assumed to be available at IMTs with each having a different volume capacity. For freight flows originating and terminating at the same zone, it is assumed that direct shipping is used. The distance for these shipments is calculated as the average of distances between the zone consolidation center and mean population centers of member counties.
Parameter values used in the model are provided in **Table 4.1** and **Table 4.2.**

**Table 4.1 Data used for model parameters**

| Parameters | Range/Values | | | | | | |
|---|---|---|---|---|---|---|---|
| | Basic Chemicals | Coal | Coal-n.e.c. | Gravel | Mixed Freight | Natural Sands | Waste/ Scrap |
| Specific Volume (ft3/ton) | 33 | 51 | 20 | 28 | 133 | 22 | 179 |
| Loading/Unloading Costs ($/ton) | 0.61-1.31 | 0.92-2.02 | 0.37-0.79 | 0.50-1.08 | 2.45-5.24 | 0.41-0.87 | 3.29-7.05 |
| Holding Costs | 100-200 | 200-250 | 100-200 | 100-200 | 500-1000 | 100-200 | 1000-2000 |

($/ton)

**Table 4.2 Data used for model parameters**

| Parameter | Range/Value |
|---|---|
| IMT Throughput Capacity (TEUs) | (3333-4167) |
| IMT Inventory Capacity (TEUs) | (333-417) |
| Pre-haul/End-haul trips (per month) | (90,000-135,000) |
| Intermodal trips (per month) | |
| (i) Rail | (1500-6000) |
| (ii) Twin 53 ft. Container Trailer Truck | (30,000-45,000) |
| (iii) 40 ft. Container Trailer Truck | (75,000-90,000) |
| Fixed Cost to Open IMT ($) | (30,000,000-40,000,000) |
| Fixed Cost Link ($) | |
| (i) Rail | (2000-3000) |
| (ii) Twin 53 ft. Container Trailer Truck | (1000-1500) |
| (iii) 40 ft. Container Trailer Truck | (800-1200) |
| Budget ($) | 2,000,000,000 |
| Mode Volume Capacity (ft3) | |
| (i) Rail | 358650 |
| (ii) Twin 53 ft. Container Trailer Truck | 7632 |
| (iii) 40 ft. Container Trailer Truck | 2391 |

In **Table 4.1**, the specific volume of the SCTG products (2-digit code classification) is deterministic and is computed by using the average densities of the constituent products. Additional volume specific to the commodity type is added to account for packing inefficiencies. In **Table 4.2**, the capacity of the modes and the budget are also deterministic. The capacity of the modes was calculated based on the size and the number of shipping containers it can haul. For example, rail has the capacity of 100-200, 40-foot containers (Fotuhi et al., 2018). The remaining parameters are selected randomly from a range of values that were determined from the data presented in the South Carolina Statewide Freight Plan (2019) and other published work. For each instance in which the optimization model was solved, a value of each parameter was selected using a uniform distribution within the range.

The final parameter that must be specified is the budget in Constraint (12). Initially, this is set at $2B that ensures this constraint is never binding; hence, this is the unconstrained case meaning unconstrained by budget to open IMT's. The model is solved using Gurobi v8.1.0 and the optimal solution includes 11 IMTs to be opened: Allendale, Columbia, Florence, Greenville, Inland Port of Dillon, Inland Port of Greer, North Augusta, Norfolk Southern & CSX North Charleston, Ridgeland, Rock Hill, and Spartanburg. The results show that on an average per month intermodal shipping share achieved is 63%.

**Figure 4.2** shows the freight volumes summed over all the time periods in the optimal solution. Since, a customer can be both a shipper and consignee/receiver, the red part of the circle represents freight volume shipped by a shipper, and the grey part represents freight volume received by a consignee. The green circles represent freight volume handled by IMTs. The highest intermodal freight is handled by Columbia at 26% followed by Florence at 19%. The highest overall intermodal share was for coal at 99% followed by coal-n.e.c.at 92%. This is because most of this freight enters from border points and is destined for longer distance hauls to PoC. The lowest overall intermodal share was for waste/scrap at 30%, followed by Gravel at 38% since most of the freight flow for these product types had the same origin as the destination (demand within a zone).

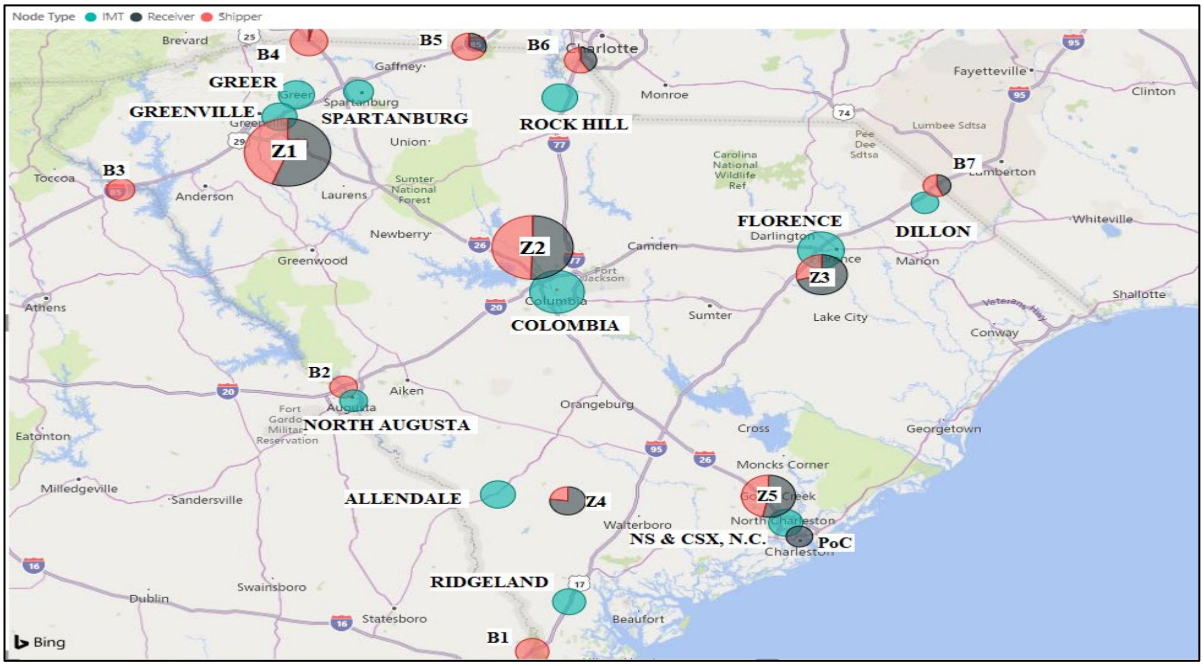


**Figure 4.2 Freight volume at shippers, consignees, and IMTs summed over all the time periods for the case study (only IMTs opened are shown)**

The results show that an IMT in Columbia is quite important. When the Columbia IMT is removed and the model is resolved, there are again 11 IMTs in the optimal solution with Clinton replacing Columbia. This is logical since Clinton is the closest possible IMT location from Columbia in the direction of the significant freight flow; however, the network performance reduced drastically. The total network cost increases by 17%, the intermodal shipping share decreases by 16%, and the average direct shipping distance increases by 39%. Columbia's location near the geographic center of the State is critical to system performance when the budget is unlimited.

## 4.4 Sensitivity analysis

### 4.4.1 Impact of budget

In practice, decision-makers rarely have an unlimited budget. The model can assist by simply reducing the available budget in the budget constraint (Constraint 12) and solving for the optimal solution. In practice, this is frequently done for several values of the maximum allowed budget for two reasons. The first is that the impact is often nonlinear with the budget so one can get significant improvement with much less investment than might be expected. The second is to see which IMTs are opened as the budget is increased. Does an increasing budget simply add additional IMTs or, at some point, do a completely different set of IMTs provide the optimal freight flow to minimize cost? Both types of information are quite valuable to a decision-maker. These ideas are illustrated using the case study data and a base case in which the budget is \$200 million. Then, the budget is varied from 25% of this base case budget to 200% and the optimal solution is obtained.

**Table 4.3 Results for Budget Sensitivity Analysis**

| Parameters | Budget (% of Base-Case Budget: $200M) | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | 25 | 50 | 75 | 100 (BC) | 125 | 150 | 175 | 200 |
| **IMTs Selected** | | | | | | | | |
| Allendale | | | | | | x | x | x |
| Clinton | | | | | | | | |
| Columbia | x | x | x | x | x | x | x | x |
| Florence | | | x | x | x | x | x | x |
| Greenville | | | | x | x | x | x | x |
| Inland Port of Dillon | | | | | | | x | x |
| Inland Port of Greer | | x | x | | x | x | x | x |
| North Augusta | | | | | | | | x |
| NS & CSX North Charleston | | | | x | x | x | x | x |
| Orangeburg | | x | | | | | | |
| Ridgeland | | | x | x | x | x | x | x |
| Rock Hill | | | | | x | x | x | x |
| Spartanburg | | | | | | | | x |
| **Number of IMTs Opened** | 1 | 3 | 4 | 5 | 7 | 8 | 9 | 11 |
| **Variable Cost Share (%)** | 99.86 | 99.45 | 99.06 | 98.75 | 98.09 | 97.75 | 97.48 | 96.87 |
| **Difference from Base-case (%)** | 51.04 | 28.51 | 6.66 | 0 | -8.61 | -10.29 | -11.21 | -12.2 |

The results are presented in **Table 4.3** and show interesting spatial results relative to South Carolina's geography. At the smallest budget percentage (25% or $50M), the only IMT is opened in Columbia which can be used to consolidate freight even though only one IMT is open. At 50% of the base-case budget, two additional IMTs are opened at the Inland Port of Greer and Orangeburg. The Inland Port of Greer serves the shippers/consignees in the upper geographical region (Z1, B3, B4, B5, and B6), Columbia serves the midlands (Z2, Z3, B2, B6, and B7), and Orangeburg serves the lower region (Z3, Z4, Z5, B1, B7, and PoC). At 75%, Florence is added, and Ridgeland replaces Orangeburg. This is understandable because Florence and Ridgeland are nearly equidistant from Orangeburg on I-95 so more budget allows the freight in the east to be more efficiently handled by two IMTs located towards the north and south rather than one in the middle.

**Figure 4.3** illustrates the nonlinear performance that can benefit decision making. The difference between 25% of the base budget that opens 1 IMT and 50% that opens 3 IMTs is that the amount of freight shipped intermodally more than doubles. The associated total network cost reduction is 22.5%. While this is important, the number of trucks that are removed from the roadways could be a significant induced impact that has positive implications beyond the original scope of this model because of the reduced congestion and decreased carbon footprint. One could imagine these benefits supporting arguments for increased budgets, for example. Further increasing the budget from 50% to 75% of the base budget yields a saving of 21.8% in total network cost; however, additionally increasing the budget from 75% to 100% produces just a 6.7% increase in savings. The savings continue to diminish more rapidly as the budget is further increased, 0.93% when the budget is increased from 150% to 175% and 0.99% when the increase is from 175% to 200%. This nonlinear trend between total network cost and budget could have an impact on decision-makers because it allows them to quantitatively evaluate the benefits associated with increasing budget levels and use this information to support budget requests.

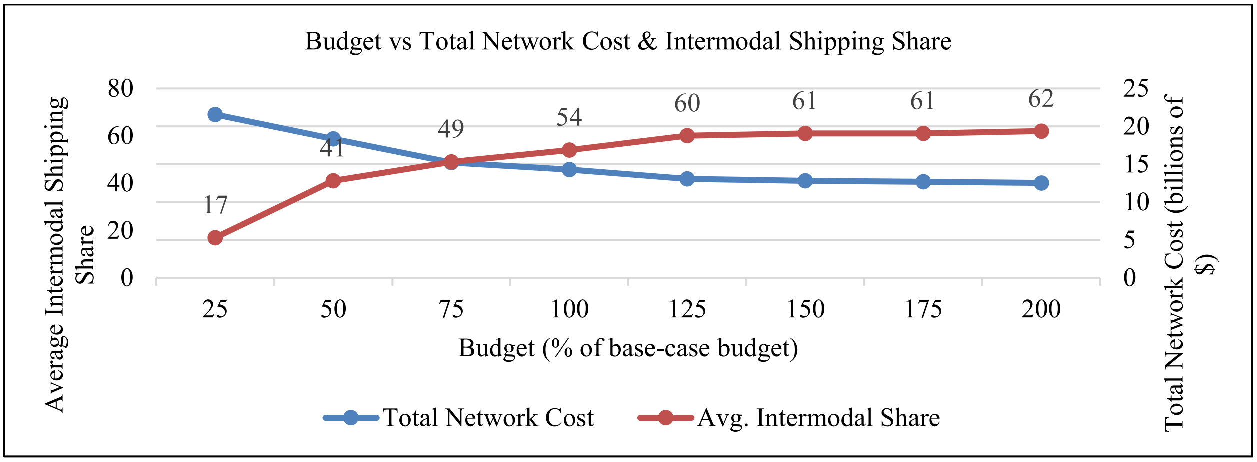



**Figure 4.3 Effect of budget on total network cost and average intermodal shipping share across the planning horizon**

## 4.4.2 Impact of restricting the number of IMTs

The model can also support a decision-maker exploring the impact of incrementally adding IMT's. By adding a constraint that limits the total number of IMT's, the model will find, for example, the combination of two or fewer IMT that minimize the total cost. By incrementally increasing the number of IMT's and dissecting the solution, insight is gained on the locations that have the most significant impact on cost as well as cost comparisons between scenarios and against the base-case scenario. **Figure 4.4** illustrates these cost comparisons for optimal solutions with ten experiments.

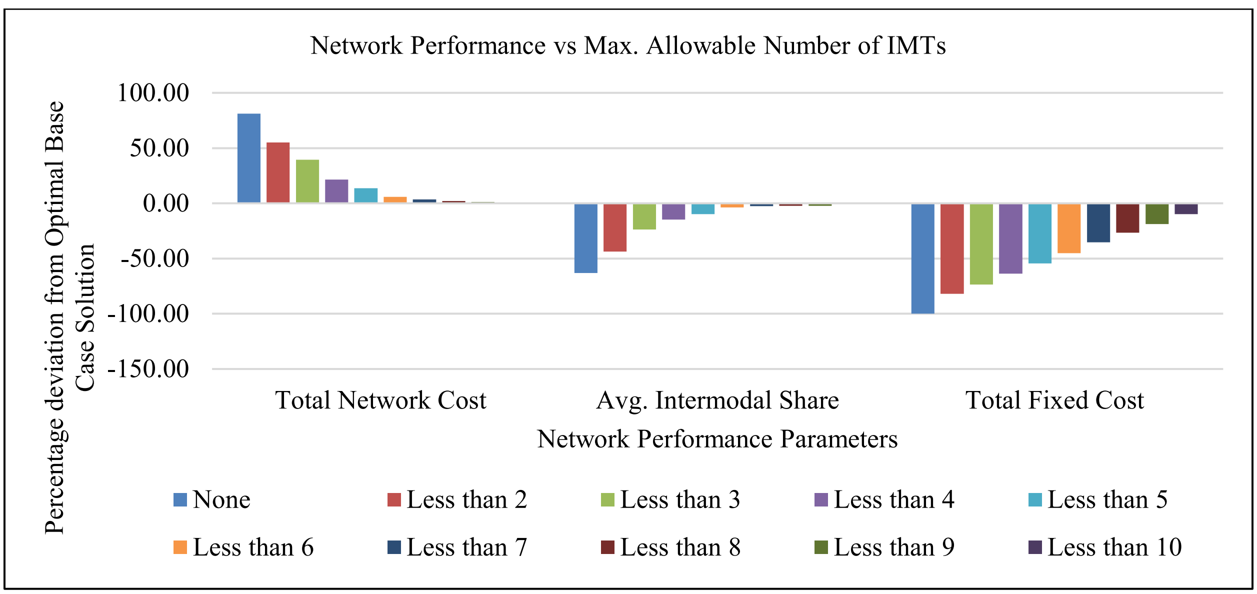



**Figure 4.4 Deviation of Total Network Cost, Average Intermodal Share, and Total Fixed Cost in percentage from Optimal base-case for different limitations on the number of IMTs**

When no IMT can be opened, all the demands are satisfied through direct shipping and the total network cost is 81% greater than the base case. When at most two IMTs are permitted, Greenville and Ridgeland are selected in the optimal solution. Greenville serves the upper half of the geographical region (Z1, Z2, Z3, B3, B4, B5, B6, and B7) while Ridgeland serves the lower half (Z3, Z4, Z5, B1, B2, B7, and PoC). In the case of a maximum of four IMTs, the Inland Port at Greer serves the upstate (Z1, B3, B4, B5), Florence serves the eastern region (Z3, Z5, B6, B7), Ridgeland serves the southern region (Z4, Z5, B1, B2, and PoC) and Columbia serves the midlands and nearby customers (Z2, B5, B6).

As we continue increasing the maximum number of IMTs allowed, the IMTs selected increase to a maximum of 11, and are opened first near the shipper/consignees having higher freight volume to be shipped or received. The solutions for less than 6, 7, 8, 9, and 10 IMTs resulted in modest improvement with the increase in total network cost at most 6% above optimal (11 IMTs) and saving in expenditure on fixed cost up to 45% from optimal (11 IMTs).

### 4.4.3 Impact of excessive demand

The FAF4 dataset gives us a network with balanced supply and demand, but often there are periods when demand exceeds the available supply for a given period. This is when holding inventory at an IMT can act as a buffer and reduce or eliminate any negative impact associated with the extra demand. To explore this, the network supply is increased to 1.5 times the original supply. Specific demand is unchanged from the base case but the total demand for mixed freight is increased for the high demand seasons. The month of October (1.75 times), November (2 times), and December (2.5 times) have increased total demand, so demands are satisfied from any shipper with available supply during these months. **Figure 4.5** shows that inventory starts to build from May to September to meet the excessive demand from October to December.

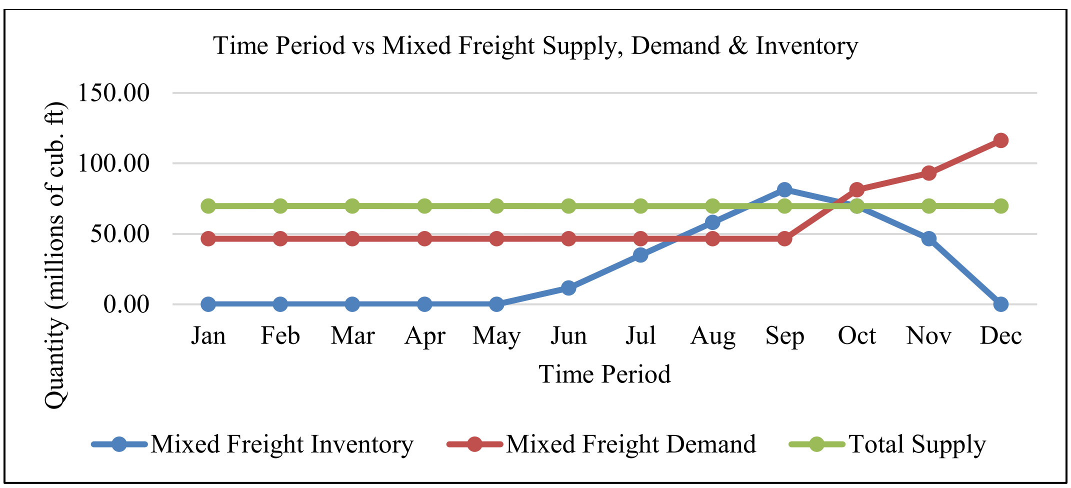



**Figure 4.5 Supply, Total Demand and Inventory for Mixed Freight over the planning horizon**

Since 72% of the total demand for mixed freight is in the upper geographical region of the state, (Z1, Z2, B4, B5, B6, B7) the model builds 95% of the total inventory in this region. **Figure 4.6** shows the highest volume of freight being held at Greenville (29%), followed by Spartanburg (27.5%), and Florence (17.7%). Therefore, to make the network robust and able to reduce the impact of excessive demands, inventory for mixed freight should be accommodated at these IMT locations. This analysis provides insight into how the model can help decision-makers influence the design of IMTs and/or nearby facilities for the locations where holding inventory can make the network more robust. Further, the model provides insights into the amount of physical space needed for storage based on demand forecast that can be varied by the decision-makers to investigate sensitivity.

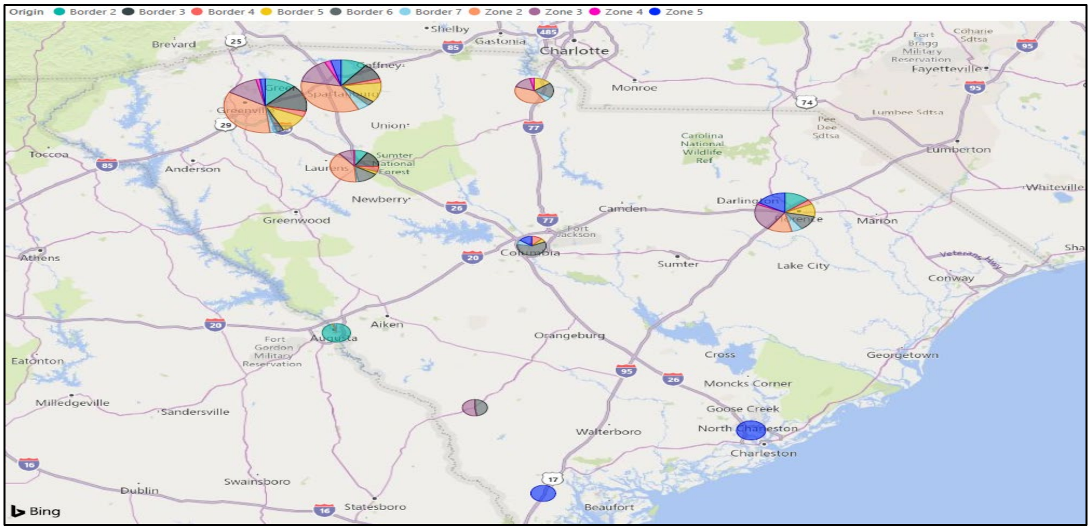



**Figure 4.6 Mixed Freight inventory across the planning horizon by volume (cub. ft.) at IMT locations with respect to the Shipper/Origin**

# CHAPTER 5

## Operational Model for Less than Truckload Carrier Collaboration

The proposed CCVRPPD for LTL carrier collaboration is a MILP model. This chapter provides a detailed description of CCVRPPD, assumptions, mathematical model, solution methodology, experimental design, and results from the experiments performed.

### 5.1 Problem description

In the proposed CCVRPPD, each carrier receives jobs directly from shippers/consignees. The carrier can retain any of these jobs it wishes to fulfill while the remainder is released to a common pool for sharing. Then, a central authority allocates the pooled transshipment (released jobs) among the alliance members by determining the optimal routes for pickup and delivery of all jobs, both retained and allocated, to be serviced by each carrier. When the carriers are allowed to retain some of their jobs, the allocation of the pooled jobs by the central authority is more complex because it needs to consider the location of the retained jobs of each of the carriers. **Figure 5.1** illustrates the described process.

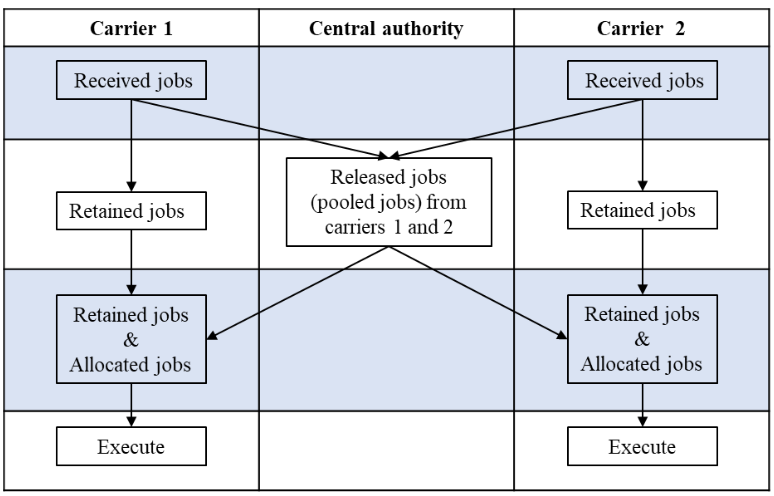



**Figure 5.1 Illustration of the proposed CCVRPPD with two carriers**

Each job is a paired pickup and delivery of goods. That is, each job consists of a customer location from where the goods should be picked up and another customer location to where the goods should be delivered. Trucks must arrive and leave at each pickup and delivery location within a specified time window. It is assumed that each carrier in the alliance will have one depot where vehicles start and end trips. It is also assumed that there is no pickup or drop off at the depots. Since the vehicles involved in this study are trucks, the two terms *"vehicle"* and *"truck"* are used interchangeably hereafter. A truck cannot serve all jobs received by a carrier because there is a limit of 14 hours of continuous service for a truck driver as per the Federal Motor Carrier Safety Administration ("Hours of Service | Federal Motor Carrier Safety Administration," ). Therefore, multiple vehicles may be needed at each depot to ensure that all jobs are served. It is assumed that there is a sufficient number of vehicles at each carrier depot to serve all jobs, retained and allocated. The vehicles are allowed to visit the pickup locations and delivery locations in any sequence on their routes; however, for each job, the pickup location must be visited before the corresponding delivery location. It is also assumed that the time that a truck stays at a node to pick up or to deliver is zero. The proposed CCVRPPD is a variant of the MDVRPPD with retained jobs that consider several real-world constraints such as multiple vehicles at each carrier depot, time windows, limited vehicle capacity, mixed pickup and delivery in a single route, and restriction on trucks' service hours.

An example of the network utilized in this study is shown in **Figure 5.2**. In this example, there are two carriers in the alliance and each carrier receives four pickup and delivery jobs each. The pickup and delivery job pair is connected by the directed arrow. It should be noted that in the optimal route, the truck does not necessarily go directly from a pickup node to a delivery node as shown in **Figure 5.2**. Example inputs for this 18-node network (1 depot and 8 customer locations for each of the two carriers) are shown in **Table 5.1**. Node 1 is the depot of carrier 1 and node 2 is the depot of carrier 2. In this example, each carrier retains 50% of its jobs.

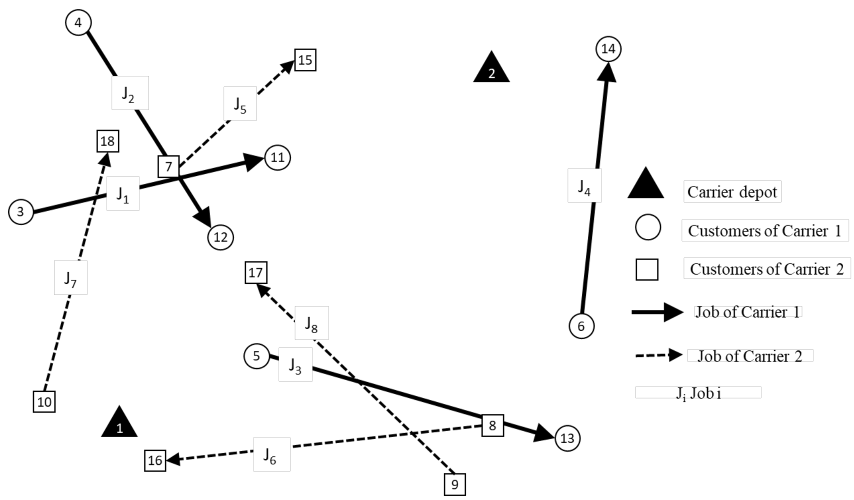



**Figure 5.2 Pickup and delivery jobs received by carrier 1 and carrier 2 for an 18-nodes network (adapted from (Dai et al., 2014))**

**Table 5.1 Pickup node, delivery node, time windows and quantity of goods of each job for an 18-nodes network (adapted from (Dai et al., 2014))**

| Job | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
|---|---|---|---|---|---|---|---|---|
| **Pickup node** | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
| **Delivery node** | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 |
| **Pickup time window** | [14, 19] | [9, 16] | [7, 17] | [14, 19] | [14, 16] | [7, 20] | [12, 17] | [7, 17] |
| **Delivery time window** | [17, 23] | [13, 20] | [9, 20] | [16, 23] | [17, 20] | [9, 24] | [16, 20] | [10, 21] |
| **Quantity of goods** | 50 | 50 | 50 | 50 | 50 | 50 | 50 | 50 |

The routes that the two carriers would have taken without collaboration are shown in **Figure 5.3a**. With collaboration, the routes could be drastically different as shown in **Figure 5.3b** since the carriers are serving a different set of jobs (retained and allocated).

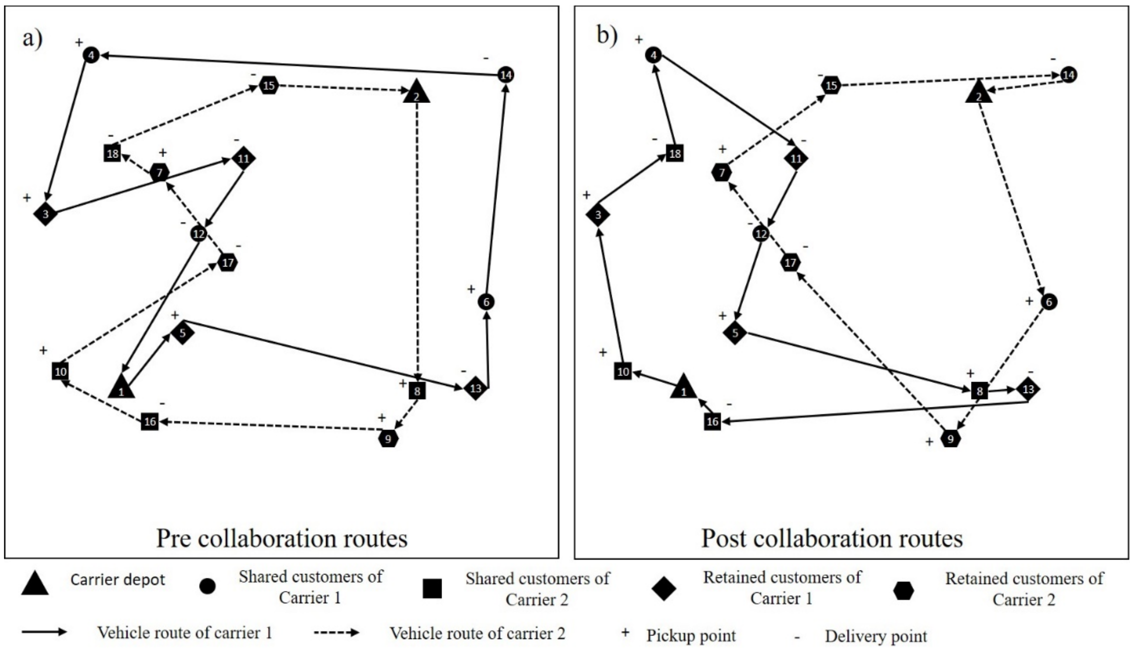



**Figure 5.3 a) Vehicle route of the illustrative example – without collaboration b) Vehicle route of the illustrative example – with collaboration**

## 5.2 Mathematical formulation

The mathematical model of CCVRPPD is defined based on a graph $G = (N, A)$. Where $N$ is the set of the total number of nodes in the network and $A$ is the set of arcs connecting each pair of nodes $i$ and $j$, $i \in N$ and $j \in N$. The set $N$ consist of carrier depot nodes and customer nodes. Since each carrier has only one depot, it should be mentioned that the set of carriers and set of carrier depots are the same and is represented as $D$. If $d$ number of carriers form a collaborative alliance, the set of all carrier depots (or set of carriers) in the alliance is denoted as $D = \{1, . . ., d\}$. Each carrier depot has $|V_f|$ number of vehicles, where $f$ represents the depot, $f \in D$ and $V_f$ is the set of vehicles at the carrier depot $f$, $f \in D$. It is assumed that |Vf| is large enough to serve all jobs, retained and allocated. From the available number of vehicles at depot f (|Vf|), the model determines the minimum number of vehicles required to serve the jobs. If the number of jobs received by the carrier $p$, $p \in D$ is $m_p$ and the total number of jobs received by all carriers in the alliance is $m$, then the set of pickup nodes is, $PK = \{d + 1, . . ., d + m_1, d + m_1 + 1, . . ., d + m_1 + m_2, d + m_1 + m_2 + 1 . . ., d + m\}$ and set of delivery nodes is $DL = \{d + m + 1, . . ., d + m + m_1, d + m + m_1 + 1, . . ., d + m + m_1 + m_2, d + m + m_1 + m_2 + 1 . . ., d + 2m\}$. The union of sets $PK$ and $DL$ is $O$ which represents the set of all customer nodes in the network. The union of sets $D$ and $O$ is denoted as $N$ which represents the set of all nodes in the network. The set of retained jobs of the carrier corresponding to the carrier depot $f$, $f \in D$ is represented as $R_f$. The cost for a vehicle to traverse the arc connecting $i$, $i \in N$, and $j$,$j \in N$ is $C_{ij}$. The quantity of freight to be picked up or delivered at node $i$, $i \in O$ is denoted as $q_i$. If $q_i$ is positive, the required service is a pickup, and if it is negative, the service is a delivery. It is assumed that all vehicles in the alliance, represented by set $V$ have the same capacity $K$. All vehicles are subjected to the same restriction on service hour and that maximum allowed is $H$. Each customer $i$, $i \in O$, has a time window, $[a_i, b_i]$, where $a_i$ is the earliest acceptable pickup/delivery time and $b_i$ is the latest. The time at which the vehicle $v$, $v \in V$ starts servicing node $i \in O$ is $S_i^v$ and the time required to travel from node $i \in N$ to node $j$

$\in N$ is $T_{ij}$. Given these, the sets, parameters, decision variables, objectives, and constraints for the CCVRPPD are as follows.

*Sets and Parameters*

| | | |
|---|---|---|
| $D$ | = | $\{1, \ldots, d\}$, set of depots |
| $PK$ | = | $\{d + 1, \ldots, d + m_1, d + m_1 + 1, \ldots, d + m_1 + m_2, d + m_1 + m_2 + 1 \ldots, d + m\}$, set of pickup nodes |
| $DL$ | = | $\{d + m + 1, \ldots, d + m + m_1, d + m + m_1 + 1, \ldots, d + m + m_1 + m_2, d + m + m_1 + m_2 + 1 \ldots, d + 2m\}$, set of delivery nodes |
| $O$ | = | $PK \cup DL$, set of all customer nodes (pickup and delivery nodes) |
| $N$ | = | $D \cup O$, set of all nodes in the network |
| $V_f$ | = | Set of vehicles at depot $f$, $f \in D$ |
| $V$ | = | $V_1 \cup V_2 \cup, \ldots, \cup V_d$, set of all vehicles where $d$ is the number of depots |
| $R_f$ | = | Set of pickup and delivery nodes of retained jobs of the carrier corresponding to depot $f$, where $f = 1, \ldots, d$ |
| $d$ | = | The total number of carrier depots is equal to the total number of carriers in the alliance (It is assumed that each carrier has only one depot) |
| $K$ | = | Vehicle capacity |
| $H$ | = | Maximum service hours allowed in one vehicle route |
| $C_{ij}$ | = | Cost of travel from node $i$ to node $j$, $i \in N, j \in N$ |
| $q_i$ | = | Demand/supply at node $i$, $i \in O$ (positive sign represents a pickup and negative sign represents a drop off) |
| $T_{ij}$ | = | The time required to traverse the arc connecting node $i$ and node $j$, $i \in N, j \in N$ |
| $a_i$ | = | The earliest acceptable pickup/ delivery time at node $i$, $i \in O$ |
| $b_i$ | = | The latest acceptable pickup/ delivery time at node $i$, $i \in O$ |
| $M$ | = | Large number |
| $m$ | = | The total number of jobs received by all carriers in the alliance |

*Decision variables*

$$x_{ij}^{v} = \begin{cases} 1 \text{ if vehicle } v \in V \text{ traverses the arc connecting } i \in N \text{ and } j \in N \\ 0 \text{ otherwise} \end{cases}$$

$Q_{ij}^{v}$ = Quantity transported across arc ($i \in N, j \in N$) by vehicle $v \in V$

$S_i^{v}$ = The time at which the vehicle $v \in V$ begins the service at node $i \in N$

*Objective*

$$\text{Min } Z = \sum_{v \in V} \sum_{i \in N} \sum_{j \in N} C_{ij} x_{ij}^{v} \tag{20}$$

*Subject to:*

$$\sum_{j \in N} x_{ji}^{v} - \sum_{j \in N} x_{ij}^{v} = 0, \quad \forall \quad i \in N, v \in V \tag{21}$$

$$\sum_{j \in O} \sum_{v \in V, v \notin V_i} x_{ij}^{v} = 0, \quad \forall \quad i \in D \tag{12}$$

$$\sum_{j \in N} x_{ij}^{v} \leq 1, \forall i \in D, v \in V \tag{22}$$

$$Q_{ij}^{v} \leq K x_{ij}^{v}, \quad \forall \quad i \in N, j \in N, v \in V \tag{23}$$

$$\sum_{v\in V}\sum_{j\in O}\left[Q_{ij}{}^{v}-Q_{ji}{}^{v}\right]=q_i,\quad \forall \quad i\in O \tag{24}$$

$$\sum_{i\in N}\sum_{j\in N}T_{ij}x_{ij}{}^{v}\le H,\ \ \forall\ \ \mathrm{v}\in V \tag{25}$$

$$x_{ij}{}^{v}=0,\quad \forall\ \ i\in D, j\in D, v\in V \tag{26}$$

$$\sum_{v\in V}\sum_{i\in N}x_{ij}^{v}=1,\ \ \forall\ \ j\in O \tag{27}$$

$$\sum_{v\in V, v\notin V_f}x_{ij}{}^{v}=0,\ \ \forall\ \ f\in D, i\in N, j\in R_f \tag{28}$$

$$S_j{}^{v}\ge S_i{}^{v}+T_{ij}x_{ij}{}^{v}-M(1-x_{ij}{}^{v}),\ \ \forall\ \ i\in N, j\in O, v\in V, i\ne j \tag{9}$$

$$a_i\le S_i^{v}\le b_i,\ \ \forall\ i\in O,\ v\in V \tag{10}$$

$$S_i^{v}\le S_{i+m}{}^{v},\ \ \forall\ \ i\in PK, v\in V \tag{11}$$

$$\sum_{j\in O}x_{ij}{}^{v}-\sum_{j\in N}x_{(i+m)j}{}^{v}=0,\quad \forall \quad i\in PK, v\in V \tag{12}$$

$$Q_{ij}{}^{v}\ge 0,\ \ \forall \quad v\in V,\ i\in N, j\in N \tag{13}$$

$$S_i^{v}\ge 0,\ \ \forall\ \ i\in N, v\in V \tag{14}$$

The objective function (20) minimizes the total relevant costs for satisfying all jobs. The meaning of each constraint is provided below.

- Constraints (21) ensure that a vehicle arriving at a node must leave the node or vice versa (including depot nodes). Constraints (22) ensure that the vehicles only start at their carrier depots. This constraint eliminates all vehicle routes that start from other carrier's depots. Constraints (23) ensure that a vehicle only begins from its depot once. They also ensure that only the required number of vehicles leave the depot and the rest stay at the depot. Constraints (21), (22), and (23) also ensure that each vehicle starts and ends at its carrier depots.
- Constraints (24) are the vehicle capacity constraints. They ensure that the vehicle capacity is never exceeded.
- Constraints (25) are flow balance across each node. They guarantee that the difference between the incoming and the outgoing products flow in a node will be equal to the supply or demand at that node.
- Constraints (26) restrict the maximum hour traveled in one vehicle route.
- Constraints (27) prohibit vehicles from traveling from one depot to another depot. This is to ensure that a truck belonging to one carrier will not use another carrier's depot.
- Constraints (28) ensure that every customer/node is visited exactly once.
- Constraints (29) ensure that the vehicles of a carrier will not serve the retained jobs of other carriers.
- Constraints (30) and (31) force the vehicles to operate within the time window constraints. Constraints (30) give the time ($S_j^v$) at which the vehicle $v$ starts from node $j \in N$, if the vehicle $v$ is going from node $i$ to node $j$. A big number $M$ makes the right-hand side negative if the arc $(i, j)$ is not active (i.e., $x_{ij}{}^{v}=0$) which ensures that the constraints (30) are only applicable for active arcs. The constraints (30) also ensure that the vehicles start and end only at the carrier depots and thus, eliminates sub tour formation. Constraints (31) ensure that the time at which a vehicle arrives/starts from a node $i \in N$ is within the

allowable time window; i.e., greater than the earliest pickup/delivery time and less than the latest pickup/delivery time of that node.

- Constraints (32) ensure that the pickup node is visited before the corresponding delivery node.
- Constraints (33) guarantee that both pickup and delivery of a job are served by the same vehicle.
- Constraints (34) and (35) are non-negativity constraints.

The CCVRPPD assumes that there is only one pickup or delivery at each customer locations. However, the model can be used even if the customers have both pickup and delivery of multiple products (e.g., consolidation center) by considering each pickup and delivery as separate customer nodes. The distance between the customer nodes, in this case, will be zero.

### 5.3 Solution methodology

The CCVRPPD described in this paper is an extension of the VRPPD; thus, it belongs to the class of NP-hard problems (Solomon, 1987). For NP-hard problems, all known algorithms that obtain an optimal solution require exponentially increasing computational time as the number of customers increases. Therefore, heuristic methods that provide approximate solutions are justified and are required for realistic-sized problems. In this study, a solution methodology is developed based on the LNS heuristic. The LNS heuristic was introduced by Shaw (1998) to solve the VRP with and without time windows. Later, several studies used this approach to solve several variants of VRP such as VRPPD, multi-depot VRP, etc. (Bent & Van Hentenryck, 2004, 2006; Kilby, Prosser, & Shaw, 2000; Y. Li, Chen, & Prins, 2016; Pisinger & Ropke, 2007; Ropke & Pisinger, 2006). The underlying principle of the LNS heuristic is to remove some jobs from the current solution and then reinsert them in a better position to improve the objective function value (Shaw, 1998). How the search operates is highly dependent on two factors: how the jobs are chosen for removal and how the removed jobs are reinserted into the route (Shaw, 1998).

**Figure 5.4** (Algorithm 1) shows how the LNS heuristic works as described by Shaw (1998) and Ropke and Pisinger (2006). Algorithm 1 requires two inputs: an initial solution and the number of jobs $q$ to be removed from the current solution in one iteration. The initial solution is obtained as in Shaw (1998) but modified for the CCVRPPD as follows. It is assumed that one vehicle route is required to serve one job and each carrier serves all of their received jobs by themselves (i.e., without collaboration). For example, if there are two carriers in the alliance and each received two jobs each from the shippers, then, there will be four vehicle routes in the initial solution; two routes that start and end at carrier depot 1 and two routes that start and end at carrier depot 2. The second input $q$ is the number of jobs to be removed from the current solution (initial solution for zero$^{th}$ iteration) and this value determines the size of the neighborhood search. It has been found that the ideal value of $q$ lies in between [0.1*$n$, 60] (Pisinger & Ropke, 2007). Based on this range and the results of preliminary experiments in this study, the $q$ value is selected to be 0.6*$n$, where $n$ is the total number of jobs in the alliance. Since the largest number of jobs considered in this study is 30, the $q$ value never exceeds the maximum limit. In line 1 of **Figure 5.4**, the initial solution is set as the best solution. The algorithm iterates from line 2 through line 8 until the stopping criterion is met. Inside the while loop, a temporary solution $s$ is initialized with the current best solution. Then, in line 4, the $q$ number of jobs is removed from $s$ using the removal heuristic (**Figure 5.5**). In line 5, the removed jobs are inserted back to $s$ using the insertion heuristic (**Figures 5.6 and 5.7**). After insertion, if the cost of route $s$ is less than that of the current best solution, then $s$ designated the new current best solution and the algorithm moved to the next iteration. In this study, the algorithm is stopped after a specified number of iterations.

**Algorithm 1: LNS heuristic**

**Input:** Initial solution, $q \in N$

1. best solution ,$s_{best}$ = Initial solution
2. **while** The stopping criteria is not met **do**
3. $s = s_{best}$
4. remove $q$ jobs from $s$
5. reinsert the removed jobs $q$ into $s$
6. **if** $f(s) < f(s_{best})$ **do**
7. $s_{best} = s$
8. **end if**
9. **end while**
10. **return** $s_{best}$

**Figure 5.4 Pseudocode for LNS heuristic**

Ropke and Pisinger (2006) modified the removal heuristic developed by Shaw (1998) to make it suitable for a VRPPD. Ropke and Pisinger's version of the removal heuristic is further adapted in this study to make it suitable for the CCVRPPD problem. The removal heuristic removes *similar* jobs from the route. A *relatedness measure* is used to find *similar* jobs. If the jobs selected for removal are different from each other, then the solution may not improve because these jobs may only be reinserted at their original positions or some other worse positions (Ropke & Pisinger, 2006). The *relatedness measure R(i, j)* of two pickup and delivery jobs depends on the distance between their pickup nodes, the distance between their delivery nodes, and the time of service at these nodes. The *relatedness measure* used in this paper is shown in Equation (36).

$$R(i,j) = (d_{A(i),A(j)} + d_{B(i),B(j)}) + (|T_{A(i)} - T_{A(j)}| + |T_{B(i)} - T_{B(j)}|) \tag{15}$$

Let $A(i)$ and $B(i)$ represent the pickup and delivery nodes of job $i$ respectively. The term $d_{A(i),A(j)}$ represents the distance between the pickup nodes of jobs $i$ and $j$. The term $d_{B(i),B(j)}$ is the distance between the delivery nodes of jobs $i$ and $j$. $T_{A(i)}$ is the time when the pickup node of $i$ is visited and $T_{B(i)}$ is the time when the delivery node of $i$ is visited. The values of $d_{A(i),A(j)}$, $d_{B(i),B(j)}$, $T_{A(i)}$, and $T_{B(i)}$ are normalized via Equation (37) such that they only take values in the range [0, 1]. The smaller the value of $R(i, j)$ the more the jobs are related. The pseudocode for removal heuristic is provided in **Figure 5.5** (Algorithm 2). The inputs required for the removal heuristic are: a solution ($s$), the number of jobs to be removed ($q$), and a parameter $p \geq 1$. First, the algorithm selects a random job ($r$) from $s$. Then, a job that is *similar* to $r$ is selected and both of these jobs are moved to list $D$. In the subsequent iterations, one job will be randomly selected from list $D$ and a job *similar* to the selected job is identified. Then, both of these jobs will be moved to list $D$. Repeat this process until the number of jobs in list $D$ is equal to $q$. The process of selecting jobs to remove is randomized by two parameters $y$ and $p \geq 1$. The value of $y$ is selected randomly from a uniform distribution in the range [0, 1] and the introduction of $y$ avoids the selection of similar sets of jobs merely based on relatedness. Randomness increases as the value of $p$ decreases and the value of $p$ is set to 4 in this study as the value of $p$ less than 3 or greater than 30 gives poor results (Shaw, 1998).

$$t = \frac{(t_i - t_{\min})}{t_{\max} - t_{\min}} \tag{16}$$

Where, $t$ is the normalized value of $d_{A(i),A(j)}$, $d_{B(i),B(j)}$, $T_{A(i)}$, or $T_{B(i)}$. The $t_i$ is the original value of $d_{A(i),A(j)}$, $d_{B(i),B(j)}$, $T_{A(i)}$, or $T_{B(i)}$. The $t_{min}$ is the minimum value among $d_{A(i),A(j)}$, $d_{B(i),B(j)}$, $T_{A(i)}$, and $T_{B(i)}$. The $t_{max}$ is the maximum value among $d_{A(i),A(j)}$, $d_{B(i),B(j)}$, $T_{A(i)}$, and $T_{B(i)}$.

**Algorithm 2: Removal heuristic**
**Input:** Solution ($s$), $q \in N$, $p \in \mathbb{R}_+$
job, $r$ = a randomly selected job from s
set of Jobs: $D = \{r\}$
**while** $|D|<q$ **do**
    $r$ = a randomly selected job from $D$
    $L$ = an array containing all jobs from $s$ but not in $D$
    sort $L$ such that
    $i < j \Rightarrow R(r, L[i]) < R(r, L[j])$
    choose a random number $y$ from the interval [0, 1]
    $D = D \cup \{L[y^p|L|]\}$
**end while**
Remove all jobs in D from s

**Figure 5.5 Pseudocode for removal heuristic (adapted from (Ropke & Pisinger, 2006))**

The CCVRPPD problem described in this study is different from the work of Ropke and Pisinger (2006) and other variants of VRP in the literature. Therefore, a new insertion heuristic (Algorithms 3 and 4) based on a basic greedy heuristic is developed. The process of insertion is illustrated using Algorithms 3 and 4 that are provided in **Figures 5.6 and 5.7** respectively. Algorithm 3 outlines how $q$ number of jobs are inserted in a route $V$ that consists of multiple depots and multiple vehicle routes at each depot. The jobs are inserted one at a time and the job to be inserted ($r$) is selected randomly from the set of removed jobs. A single-vehicle route $k$ at the depot of carrier $c$ ($V_c^k$) is selected from route $V$. If job $r$ is not a retained job of carriers in the alliance other than carrier $c$, using algorithm 4, the best positions of pickup and delivery nodes of job $r$ in $V_c^k$ is determined. A copy of route $V$ is created as a temporary route $V_{temp}$. The route $V_c^k$ in $V_{temp}$ is replaced with the new route obtained from algorithm 4 and the $V_{temp}$ is stored in array $L$. This process is repeated for all single-vehicle routes in $V$. The route with the minimum cost in array $L$ is selected as the current best route and this is designated as route $V$ for the next iteration. This process is repeated until all removed jobs are reinserted in the route.

Algorithm 4 discusses how the pickup and delivery nodes of a job $r$ are inserted at its best position in a single-vehicle route $V_c^k$. A *position* for insertion is available between any two consecutive nodes (including depot nodes and customer nodes) in the route $V_c^k$. First, the pickup node of job $r$ is inserted at all possible *positions*. A new route is created for each insertion and is stored in an array $S$. Then, for all routes in array $S$, the delivery node of job $r$ is inserted after the pickup node of job $r$ at all possible *positions,* and these routes are stored in array $S'$. It is verified that each route in array $S'$ satisfies the constraints such as time window, vehicle capacity, and maximum hour in a vehicle route. If not, those routes are then removed, and the best route is selected as the route with minimum cost in array $S'$.

**Algorithm 3: Insert *q* number of jobs in a vehicle route *V***

```
Input:
    V = Initial vehicle route that does not consist the removed jobs,
    q = Number of removed jobs
    Q = Set of all removed jobs = {1, 2, ..., q}
    F = Set of all carriers in the alliance
while |q| > 0 do
    r = randomly selected job from Q
    Array, L = [ ]
    for all c ∈ F do
        rt_c = set of all retained jobs of all carriers in the alliance except carrier c
        V_c = set of vehicle routes of carrier c in V
        for all k ∈ V_c do
            V_c^k = vehicle route k of carrier c in route V
            if r is not in rt_c do
                V_temp = V
                New_route = insert job r at its best position of route V_c^k using Algorithm 4
                Replace V_c^k with New_route in V_temp
                Add V_temp in array L
            end if
        end for
    end for
    V = minimum cost route in L
    remove r from Q
end while
return V
```

**Figure 5.6 Pseudocode for inserting *q* number of jobs in a vehicle route**

**Algorithm 4: Insert a job $r$ at its best position in vehicle route $v_c^k$**

**Input:**

Set of positions available between the nodes in route $v_c^k = N$
$r_p$ = the pickup node of job $r$
$r_d$ = the delivery node of job $r$
$H$ = Maximum hour allowed in one vehicle route
$K$ = Vehicle capacity
$a_i$ = The earliest acceptable pickup/ delivery time at node $i$
$b_i$ = The latest acceptable pickup/ delivery time at node $i$

```
Array, S = [ ]
for all positions, p ∈ N do
    New_route = insert r_p at position p of route v_c^k
    Add New_route to array S
end for
Array, S′ = [ ]
for all routes, k ∈ S do
    In route k, the position of node r_p is j
    N_k = set of all positions available between the nodes in route k
    for all positions, p ∈ N_k do
        if p ≥ j do
            New_route = insert r_d at position p of route k ∈ S
            Add New_route to S′
        end if
    end for
end for
for all routes, k ∈ S′ do
    if The total travel time from start-depot to end-depot > H do
        Remove route k from S′
    end if
end for
for all routes, k ∈ S′ do
    for all nodes, i ∈ k do
        if vehicle load at node i > K do
            Remove route k form S′
        end if
    end for
end for
for all routes, k ∈ S′ do
    for all nodes, i ∈ k do
        if arrival time at node i < a_i do
            Remove route k from S′
        end if
    end for
end for
For all routes, k ∈ S′ do
    For all nodes, i ∈ k do
        If arrival time at node i > b_i do
            Remove route k from S′
        end if
    end for
end for
Best_route = minimum cost route in S′
Return Best_route
```

**Figure 5.7 Pseudocode for inserting a job at its best position in a route**

### 5.4 Experimental design

Seven sets of analyses are performed to evaluate the performance of the proposed CCVRPPD model and cost savings under different collaboration scenarios. Analysis 1 compares solutions from the LNS heuristic to solutions from Gurobi Solver. Analysis 2 evaluates the effect of network size on cost savings. Analysis 3 evaluates the effect of the percentage of retained jobs on cost savings. Analysis 4 evaluates the effect of distance between the carrier depots on cost savings. Analysis 5 evaluates the distribution of jobs to the carriers under the proposed CCVRPPD with different percentages of jobs retained. Analysis 6 evaluates the effect of the size of overlapping carrier regions on cost savings, and analysis 7 evaluates the effect of the number of jobs in the overlapping carrier region on cost savings. The experiments are conducted on a desktop computer equipped with a 3.40 GHz processor and 8 GB RAM. The LNS heuristic algorithm is coded in Python (version 3.6).

The assumptions and parameter values used in the experiments are as follows. All jobs consist of transporting 50 units of goods between an origin and destination pair and the vehicle capacity is 300 units for all vehicles. The "cost" to traverse the arc between any two nodes is defined to be proportional to the distance between them. The travel time between any two nodes is calculated by dividing the distance between the nodes by an average truck speed of 89 kilometers per hour. The earliest arrival time of pickup locations is randomly generated from the uniform distribution in the range [7, 15] hours, where 7 corresponds to 7 AM. The earliest arrival time of the delivery locations is calculated by adding a random number between 2 and 5 hours to the earliest arrival time of the job's pickup location. The latest departure time of the pickup locations is randomly generated from the uniform distribution in the range [16, 22] hours. The latest departure time of the delivery locations is calculated by adding a random number between 2 and 5 hours to the latest departure time of the job's pickup location. The maximum value of the latest departure time at all delivery locations is 24 hours and it is assumed that there is no restriction on the time when a truck must return to the depot. In actual practice, carriers would decide on which jobs to retain. In this study, it is assumed that the carriers retain the jobs that are geographically closest to their depot. This is determined by calculating the total distance for each received job, which is the sum of the distance between the carrier depot and pickup node of the job and the distance between the carrier depot and delivery node of the job. The total number of nodes in a network is calculated by adding the number of carrier depots to the number of customer locations. If there are $n$ received jobs, then the total number of customer locations will be equal to $2*n$ (because each job consists of a pickup location and a delivery location).

For analyses 1, 2, 3, 4, and 5, the experiments are conducted on networks generated by randomly locating nodes on a 2D plane of size 200-miles by 200-miles (1 mile = 1609.34 meters). That is, the $X$ and $Y$ coordinates of a node are obtained from the uniform distribution [0, 200]. For these analyses, there are two carriers in the alliance.

For analyses 1 and 2, it is assumed that both carriers retain 50% of their received jobs. Analysis 1 consists of 17 experiments (numbered 1 to 17) with networks that vary in size from 18 nodes to 50 nodes. For this analysis, only one instance is generated for each of the 17 experiments as the goal is to compare the solutions from Gurobi and LNS heuristic. Analysis 2 also consists of 17 experiments (numbered 18 to 34) with networks that vary in size from 18 nodes to 50 nodes. For analysis 2, 15 instances are generated for each of the 17 experiments. For all experiments in analyses 1 and 2, it is assumed that the depot locations of the two carriers are fixed; the coordinate of carrier 1 depot is (50, 50) and coordinate of carrier 2 depot is (150, 150). The number of jobs received (from shippers/consignees) by each carrier in each of these experiments is shown in **Tables 5.2 and 5.3**.

Analyses 3, 4, and 5 are performed on 15 different networks, each consisting of 48 customer locations; thus, each carrier has 24 customers or 12 jobs. The experiments for each of these 15 networks are numbered from 35 to 49. For each of these 15 networks, 3 different depot layouts, and 5 different levels of the percentage of jobs retained (10%, 30%, 50%, 70%, and 90%) are examined, for a total of 15 different combinations as shown in **Table 5.4**. The distance between two carrier depots in depot layout 1 is 282.84 miles, in depot layout 2 is 141.42 miles, and in depot layout 3 is 100 miles (1 mile = 1609.34 meters).
The three depot layouts are:

- Depot layout 1 - coordinate of carrier 1 depot is (0, 0) and coordinate of carrier 2 depot is (200, 200).
- Depot layout 2 – coordinate of carrier 1 depot is (50, 50) and coordinate of carrier 2 depot is (150, 150).
- Depot layout 3 - coordinate of carrier 1 depot is (50, 100) and coordinate of carrier 2 depot is (150, 100).

Analysis 6 is performed based on the work of Berger and Bierwirth (2010). However, the benchmark problem (R1_4_1) developed by Gehring & Homberger (2013) is used to generate the test instances for both analyses 6 and 7 instead of Solomon *R101* which is used in the work of Berger and Bierwirth (2010). The R1_4_1 consists of 401 nodes located in a 200-mile by 200-mile (1 mile = 1609.34 meters) square area. For this analysis, there are three carriers in the alliance. The locations of carrier depots are manually selected from the 401 nodes and they are fixed for all experiments. The coordinate of carrier 1 depot is (31, 79), the coordinate of carrier 2 depot is (171, 36), and the coordinate of carrier 3 depot is (146, 166). These three nodes are then removed from the set of 401 nodes. Analysis 6 consists of 10 experiments (numbered 50 to 59) and 15 instances are generated for each of the 10 experiments. Each instance consists of 60 customer locations that are randomly selected from the remaining 398 nodes. That means 20 customer locations (10 jobs) for each carrier. Based on the degree of competition among the carriers, Berger and Bierwirth (2010) defined three spatial scenarios: identical, adjacent, and overlapping as illustrated in **Figure 5.8**. Unlike the work of Berger and Bierwirth, the changes in benefits concerning the size of the overlapping region and the number of jobs in the overlapping region are also evaluated. In the identical scenario (**Figure 5.8a**), all carrier's customers are located throughout the entire study area; this scenario represents the highest level of competition. In this scenario, all three carriers' customer locations are selected randomly from the remaining 398 nodes and this is referred to as experiment number 50. In the adjacent scenario, each carrier's customers are primarily located in its area, and thus, there is only a little competition between the carriers. In this scenario, the 200-mile by 200-mile (1 mile = 1609.34 meters) area is divided into three equal areas as shown in **Figure 5.8b**. Then, the customer locations are drawn from the respective carrier region for each carrier. This is referred to as experiment number 51. In the overlapping scenario, each carrier's customers are located in its area and some are located in the overlapping region (**Figure 5.8c**). The level of competition is higher than adjacent and less than identical under this scenario. Since the carriers have a common region where customers could be shared more easily, more savings can be expected under this scenario than adjacent. To determine how the cost savings change for the size of the overlapping region, 8 experiments (numbered 52 to 59) are conducted by considering 8 overlapping regions that vary in size. The first overlapping region is formed by taking equal areas from each carrier region and combined them as a triangle. Then the other seven overlapping regions are formed by sizing up/down (three are formed by sizing up and four by sizing down) the original overlapping region. In all 8 of these experiments, for each of the carriers, it is assumed that 6 jobs are from the exclusive region and 4 jobs are from the overlapping region. That means, out of 30 jobs, 12 jobs are in the overlapping region.

For analysis 7, three experiments (numbered 60 to 62) are conducted by considering three different proportions of jobs in the exclusive and overlapping region. The size of the overlapping region is chosen to be the same as that of experiment 55. The different proportions of jobs are: 1) 18 jobs in the exclusive carrier region and 12 jobs in the overlapping region, 2) 21 jobs in the exclusive carrier region and 9 jobs in the overlapping region, and 3) 24 jobs in the exclusive carrier region and 6 jobs in the overlapping region. A total of 15 instances are generated for each of the three experiments.

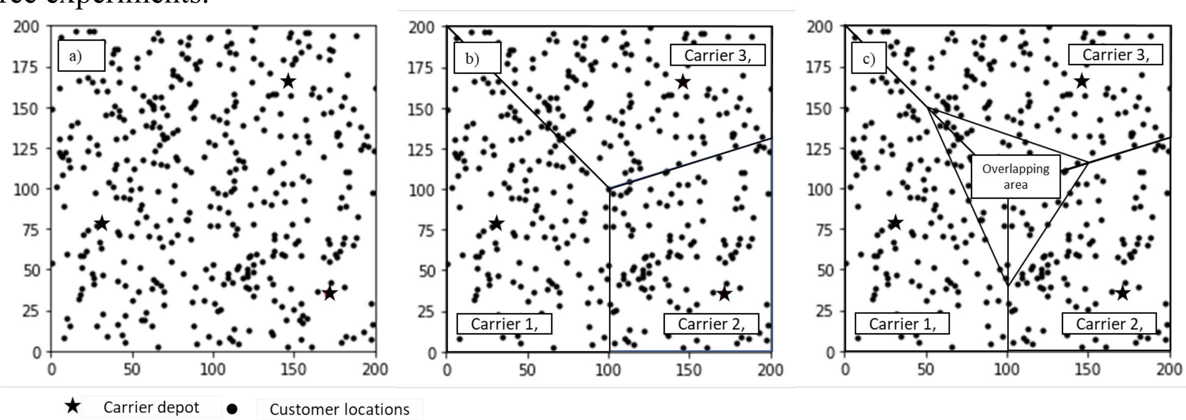



**Figure 5.8 Network layout representing the level of competition: a) identical, b) adjacent c) overlapping**

## 5.5 Results and discussion

### 5.5.1 Evaluation of LNS heuristic performance against Gurobi solver

The CCVRPPD developed in this research is solved using both the LNS heuristic and Gurobi Solver. The results of the 17 experiments are shown in **Table 5.2**, which is organized as follows. The first column shows the experiment number. The second column shows the network size that is represented in terms of the number of nodes in the network. Columns 3 and 4 show the number of jobs received (from shippers/consignees) by each carrier. Columns 5 and 6 show the total transportation cost obtained and the time taken by Gurobi Solver respectively. Columns 7 and 8 show the total transportation cost obtained and the time taken to solve the model using the LNS heuristic respectively. When Gurobi was used, runs were limited to 24 hours, and all other parameters are set as default. In **Table 5.2**, when Gurobi obtained the optimal solution, it is denoted with "*" whereas when the 24-hour maximum time was exceeded, the best solution that had been obtained is reported with an "i". It can be seen that the LNS heuristic yields optimal solutions for problem instances up to networks of size 24. Beyond that, it yields good solutions in a reasonable amount of time (less than 7.5 minutes for the 50-node network). On the other hand, the Gurobi Solver could not provide a feasible solution for networks of size 40 or more within 24 hours. It can also be observed that the computation time of the Gurobi Solver increases significantly as the network size increases. For networks of sizes 26, 32, 34, and 36 nodes, the LNS heuristic provided a better solution than the incumbent solution provided by the Gurobi Solver.

**Table 5.2 Evaluation of the performance of LNS heuristic against Gurobi Solver**

| Experiment # | Network size (# of nodes) | Number of jobs received | | Gurobi Solver (24-hours time limit) | | LNS heuristic (1000 iterations) | |
|---|---|---|---|---|---|---|---|
| | | Carrier 1 | Carrier2 | Cost | Time | Cost | time |
| 1 | 18 | 4 | 4 | 1262* | 0:01:58 | 1262 | 0:00:14 |
| 2 | 20 | 5 | 4 | 1314* | 03:56:28 | 1314 | 0:00:53 |
| 3 | 22 | 5 | 5 | 1253* | 09:33:52 | 1253 | 0:01:12 |
| 4 | 24 | 6 | 5 | 1218* | 12:22:12 | 1218 | 0:01:28 |
| 5 | 26 | 6 | 6 | 1624[i] | 24:00:00 | 1487 | 0:01:56 |
| 6 | 28 | 7 | 6 | 1358* | 08:40:18 | 1358 | 0:02:45 |
| 7 | 30 | 7 | 7 | 1308[i] | 24:00:00 | 1308 | 0:03:48 |
| 8 | 32 | 8 | 7 | 1501[i] | 24:00:00 | 1499 | 0:04:05 |
| 9 | 34 | 8 | 8 | 1829[i] | 24:00:00 | 1727 | 0:05:34 |
| 10 | 36 | 9 | 8 | 1813[i] | 24:00:00 | 1723 | 0:05:19 |
| 11 | 38 | 9 | 9 | N/A | | 1927 | 0:06:14 |
| 12 | 40 | 10 | 9 | 2035[i] | 24:00:00 | 1900 | 0:06:49 |
| 13 | 42 | 10 | 10 | N/A | | 1865 | 0:06:52 |
| 14 | 44 | 11 | 10 | N/A | | 1838 | 0:06:44 |
| 15 | 46 | 11 | 11 | N/A | | 1933 | 0:06:50 |
| 16 | 48 | 12 | 11 | N/A | | 2131 | 0:07:15 |
| 17 | 50 | 12 | 12 | N/A | | 2163 | 0:07:12 |

* optimal solution, [i] incumbent solution from Gurobi Solver, N/A - No feasible solution is found within the specified time limit

### 5.5.2 Effect of network size on cost savings from collaboration

The effect of network size on carrier collaboration is studied in analysis 2 and the results obtained are shown in **Table 5.3** which is organized as follows. Column 1 shows the experiment number. Column 2 shows the network size that is represented in terms of the number of nodes in the network. Columns 3 and 4 show the number of jobs received (from shippers/consignees) by each carrier. In column 5, the average percentage of savings of the 15 instances is presented. The minimum value, maximum value, and the standard deviation of percentage of savings of 15 instances are shown in columns 6, 7, and 8 respectively. In the 255 instances tested (15 instances for each of the 17 experiments), all of the calculated cost savings are positive. That means collaboration provided a lower cost solution than if all carriers were to operate independently. This finding is consistent with those reported in the literature (Dai & Chen, 2012; Gansterer et al., 2017; Krajewska et al., 2008; Vaziri et al., 2019). There is no specific trend in the average percentage of savings as the network size increases. The cost savings vary from 11.66% to 17.20% when 50% of the jobs are retained by each carrier. From the 15 instances tested for each network size, it is observed that the cost savings vary with the spatial distribution of the nodes in the network even if the size of the network is the same. However, the minimum percentage of savings tends to increase (column 6 of **Table 5.3**) and the maximum percentage of savings tends to decrease (column 7 of **Table 5.4**) as the network size increases. In other words, the range of savings (i.e., the difference between the maximum and minimum cost savings from the 15 instances tested) decreases as the network size increases as shown in **Figure 5.9**. This could be one of the reasons that the cost savings is not showing any specific trend when the average of 15 instances is calculated for each of the network sizes. These findings suggest that the change in cost savings for the spatial distribution of the nodes in the network decreases as the network size increases. This is confirmed from the standard deviation reported in column 8 of **Table 5.3**. The standard deviation of the percentage of savings of 15 instances tends to decrease as the network size increases. It should be noted that, no matter how small the network size is, there are savings from collaboration. From the inspection of the routes with and without collaboration, it is observed that when carriers collaborate, the number of vehicle routes is reduced, the length of vehicle miles traveled is reduced, the vehicle capacity utilization is improved, and the empty miles are reduced.

**Table 5.3 Average percentage of savings by network size**

| Experiment # | Network size (# of nodes) | Number of jobs received | | Average percentage of savings*** (%) | Percentage of cost savings** | | Standard deviation* |
|---|---|---|---|---|---|---|---|
| | | Carrier 1 | Carrier2 | | Min* (%) | Max* (%) | |
| 18 | 18 | 4 | 4 | 11.66 | 1.53 | 22.33 | 6.43 |
| 19 | 20 | 5 | 4 | 12.48 | 1.53 | 25.98 | 7.54 |
| 20 | 22 | 5 | 5 | 14.43 | 3.42 | 30.75 | 7.91 |
| 21 | 24 | 6 | 5 | 13.91 | 2.30 | 27.68 | 7.39 |
| 22 | 26 | 6 | 6 | 16.04 | 1.71 | 31.03 | 8.29 |
| 23 | 28 | 7 | 6 | 15.31 | 4.78 | 31.32 | 7.29 |
| 24 | 30 | 7 | 7 | 14.30 | 2.35 | 33.24 | 7.93 |
| 25 | 32 | 8 | 7 | 14.67 | 6.19 | 23.64 | 4.94 |
| 26 | 34 | 8 | 8 | 14.97 | 3.34 | 28.99 | 8.81 |
| 27 | 36 | 9 | 8 | 16.52 | 3.40 | 24.01 | 5.58 |
| 28 | 38 | 9 | 9 | 17.20 | 10.41 | 31.71 | 5.31 |
| 29 | 40 | 10 | 9 | 14.26 | 3.18 | 21.55 | 5.93 |
| 30 | 42 | 10 | 10 | 15.06 | 7.81 | 24.09 | 4.08 |
| 31 | 44 | 11 | 10 | 14.62 | 11.54 | 20.71 | 2.66 |
| 32 | 46 | 11 | 11 | 14.48 | 7.30 | 19.46 | 3.90 |
| 33 | 48 | 12 | 11 | 14.76 | 9.66 | 19.86 | 3.03 |
| 34 | 50 | 12 | 12 | 13.88 | 6.82 | 19.86 | 4.50 |

*minimum, maximum and standard deviation of percentage of savings for all 15 instances

** $\text{Percentage of cost savings} = \left(\frac{\text{cost before collaboration - cost after collaboration}}{\text{cost before collaboration}}\right) \times 100$

*** Average percentage of savings =(sum of the percentage of cost savings of all 15 instances /15).

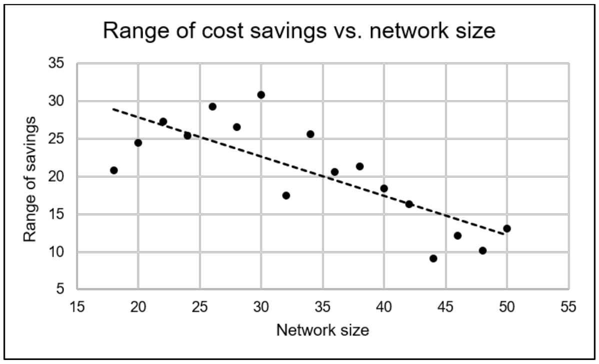



**Figure 5.9 Relationship between the range of cost savings and the network size**

### 5.5.3 Effect of percentage of retained jobs on cost savings from collaboration

The effect of the percentage of retained jobs on cost savings from collaboration is studied in analysis 3 and the results obtained are shown in **Table 5.4** and **Figure 5.10**. **Table 5.4** is organized as follows. Column 1 shows the carrier depot layout number. Columns 2 through 6 show the average percentage of savings obtained for five different percentages of retained jobs. For each percentage of jobs retained, 45 instances (3 depot layouts and 15 instances for each of the 3 depot layouts) are tested and it is observed that the percentage of cost savings decreases as the percentage of retained jobs increases. **Figure 5.10** shows that this trend is consistent even when the customer and depot locations change. The decrease in the average percentage of cost savings for a 20% increase in job retention varies between 1.42% to 9.47% depending on the customer and depot locations. However, the decrease in the percentage of cost savings to the increase in the percentage of retained jobs is not linear; the average decrease in cost savings when the percentage of retained jobs increases from 10 to 30 is 2% and it is 6.6% when the percentage of retained jobs increases from 70 to 90%. Nevertheless, in some instances, 10-15% of savings are obtained even with 90% of job retention. This implies that collaboration can provide significant cost savings even when carriers share a small fraction of their jobs. The significant savings are often realized when the locations of the pooled and retained jobs are favorable to efficient groupings.

**Table 5.4 Average percentage of savings for 10%, 30%, 50%, 70% and 90% of retained jobs under three depot layouts**

| Depot layout # / Percentage of jobs retained | The average percentage of savings of 15 instances | | | | |
|---|---|---|---|---|---|
| | 10% (35-49)* | 30% (35-49)* | 50% (35-49)* | 70% (35-49)* | 90% (35-49)* |
| **Depot layout 1** | 28.30% | 26.88% | 22.14% | 18.86% | 9.39% |
| **Depot layout 2** | 21.33% | 19.25% | 16.61% | 11.79% | 6.14% |
| **Depot layout 3** | 19.61% | 16.95% | 12.75% | 9.41% | 4.82% |

*The numbers in the parenthesis indicate the experiment numbers.

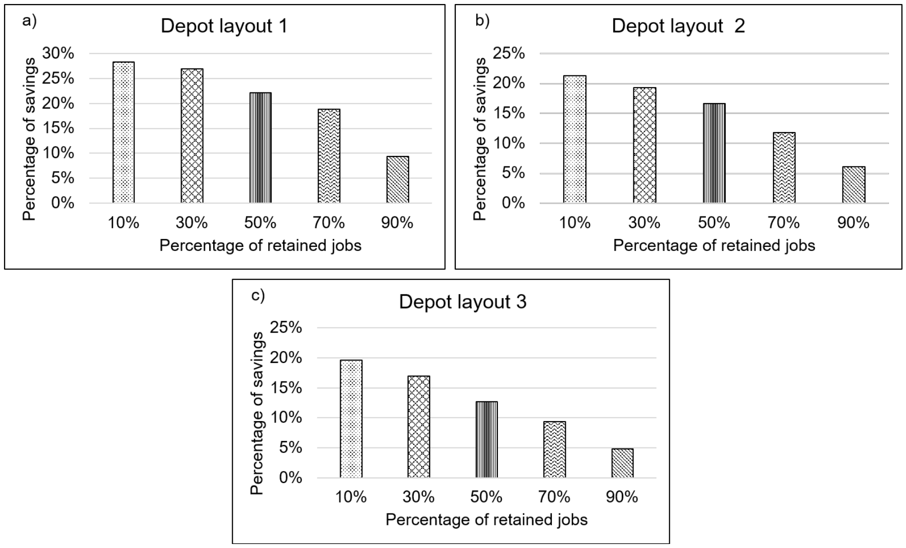



**Figure 5.10 Average percentage of savings for 10%, 30%, 50%, 70% and 90% of retained jobs for a) depot layout 1 b) depot layout 2 and c) depot layout 3**

### 5.5.4 Effect of carrier depot locations on cost savings from collaboration

The effect of carrier depot locations on cost savings from the collaboration is studied in analysis 4 and the results are shown in **Table 5.5** which is organized as follows. Column 1 shows the percentage of retained jobs. Columns 2 through 4 show the difference in cost savings between any two depot layouts. Here, the distance between the carrier depots in depot layout 1 is 2 times higher than that of depot layout 2 and 2.82 times higher than that of depot layout 3. Each depot layout is tested for 75 instances (5 percentage of retained jobs for each of the 15 instances) and the observations are as follows. The increase in savings when the distance between the carrier depots increases 1.41 times is between 1.32% to 3.86% and the increase in savings when the distance between the carrier depots increases 2 times is between 3.25% to 7.63%. Whereas, the increase in savings when the distance between the carrier depots increases 2.82 times is between 4.57% to 9.93%. Therefore, the location of the carrier depots significantly affects the total savings from carrier collaboration and more savings are obtained if the depots are located far apart from each other.

**Table 5.5 Effect of carrier depot locations on Cost Savings from Collaboration**

| **Percentage of jobs retained** | ***Difference in average cost savings between the depot layouts** | | |
|---|---|---|---|
| | **1 and 2** | **1 and 3** | **2 and 3** |
| **10** | 6.97% | 8.69% | 1.72% |
| **30** | 7.63% | 9.93% | 2.30% |
| **50** | 5.53% | 9.39% | 3.86% |
| **70** | 7.07% | 9.45% | 2.38% |
| **90** | 3.25% | 4.57% | 1.32% |

*The difference in cost savings (average of 15 instances) between the depot layouts

### 5.5.5 Distribution of jobs under the proposed CCVRPPD with different percentages of jobs retained

The distribution of jobs under the proposed CCVRPPD with different percentages of retained jobs is studied in analysis 5 and the results obtained are shown in **Table 5.6** which is organized as follows. Column 1 shows the carrier depot layout number while columns 2 through 6 show the average *Ratio* obtained for five different percentages of retained jobs. The *Ratio* is a measure of the evenness in the distribution of jobs among carriers and it is determined using Equation (38).

$$Ratio = \frac{L}{U} \qquad (3817)$$

Where,

$L$ =The number of jobs received (summation of the retained jobs and the jobs allocated from the common pool) by the carrier that received the lower number of jobs after collaboration.

$U$ =The number of jobs received (summation of the retained jobs and the jobs allocated from the common pool) by the carrier that received the higher number of jobs after collaboration.

**Table 5.6 Average *Ratio* for 10%, 30%, 50%, 70% and 90% of retained jobs under three depot layouts**

| Depot layout # / Percentage of jobs retained | Average *Ratio* | | | | |
|---|---|---|---|---|---|
| | 10% (35-49)* | 30% (35-49)* | 50% (35-49)* | 70% (35-49)* | 90% (35-49)* |
| **Depot layout 1** | 0.59 | 0.66 | 0.81 | 0.90 | 0.90 |
| **Depot layout 2** | 0.57 | 0.70 | 0.71 | 0.79 | 0.91 |
| **Depot layout 3** | 0.56 | 0.70 | 0.71 | 0.84 | 0.90 |

It is observed that the *Ratio* increases as the percentage of jobs retained increases (the *Ratio* takes the value from 0 to 1). A low *Ratio* means that the job allocation is imbalanced, and a high *Ratio* means that the job allocation is balanced. For example, a ratio of 0.5 means that one carrier has twice the number of jobs than that of the other carrier, and a ratio of 1 means that both carriers have the same number of jobs. When more jobs are retained, each carrier has more nodes scattered all over the service area and, hence, the optimal allocation of the pooled jobs naturally splits more evenly. A 20% increase in job retention leads to an increase in the *Ratio* between 1% and 15%. It is also observed that there are some instances where the job allocation is highly imbalanced at a lower percentage of jobs retained. An extreme example is shown in **Figure 5.11** where carrier 2 received only three jobs at 10% jobs retained. There are a couple of reasons for this: 1) most of the customer nodes are located near the depot of carrier 1, and 2) for those customer nodes located near the depot of carrier 2, their corresponding pickup or delivery nodes are located far away from them.

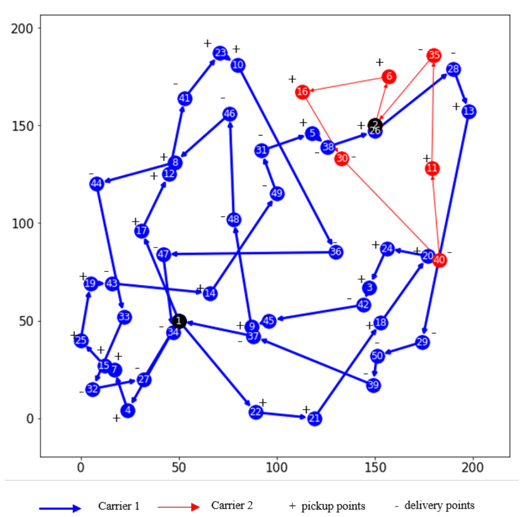



**Figure 5.11 An example of imbalanced job allocation for a network with 10% of retained jobs**

### 5.5.6 Effect of size of overlapping region on savings from carrier collaboration

The effect of the size of the overlapping region on savings from the collaboration is studied in analysis 6 and the results are provided in **Table 5.7** which is organized as follows. In column 1, the description of the value is provided whether it is the average percentage of savings, minimum value, or maximum value. Column 2 shows the results from the identical scenario where the size of the overlapping region is 100% of the total area. In columns, 3 through 10, the average percentage of savings obtained from the 8 experiments with the various sizes of overlapping regions is provided. The last column shows the results for the adjacent scenario where the size of the overlapping region is 0% of the total area. **Table 5.6** shows that the highest percentage of savings is obtained in the identical scenario where the competition is highest (all carrier's customers are located throughout the entire study area). When there is high competition, the carriers have more opportunities for collaboration, and thus, reduce the total cost. The smallest cost savings occur in the adjacent scenario where the competition is lowest (each carrier's customers are primarily located in its area). In this scenario, only the reallocation of those jobs located near the boundary of the carrier regions is beneficial; thus, there are limited opportunities. The cost savings obtained from the overlapping scenario lies between that of adjacent and identical. However, the savings increase non-linearly as the size of the overlapping region increases; the increase in savings when the size of the overlapping region increases from 0%(adjacent) to 6.75% is 13.59% (from 1.58 to 15.17), and the increase in savings when the size of overlapping region increases from 31.7% to 100% (identical) is only 2.7% (from 21 to 23.7). From this finding, it can be inferred that if carriers have a significant number of jobs in the overlapping region for reallocation, then there will be more opportunities to share the jobs between carriers even if the size of the overlapping region is small. Therefore, significant benefits can be obtained even when carriers designate a small area where jobs can be shared.

**Table 5.7 Changes in the percentage of savings with the size of the overlapping region**

| | Identical | Overlapping | | | | | | | | Adjacent |
|---|---|---|---|---|---|---|---|---|---|---|
| | | Size of the overlapping region (% of total area 200X200) | | | | | | | | |
| | (#50)* | 31.7 (#52)* | 27 (#53)* | 22.7 (#54)* | 18.75 (#55)* | 15 (#56)* | 12 (#47)* | 9 (#58)* | 6.75 (#59)* | (#51)* |
| **Average savings (%)** | 23.7 | 21.0 | 18.5 | 17.6 | 17.2 | 16.7 | 16.9 | 16.99 | 15.17 | 1.58 |
| **Min (%)** | 15.9 | 13.5 | 12.2 | 9.4 | 7.6 | 8.8 | 13.2 | 13.3 | 6.1 | 0 |
| **Max (%)** | 32.2 | 30.0 | 28.8 | 24.8 | 24.8 | 22.3 | 22.87 | 20.7 | 20.36 | 4.34 |

* The number in the parenthesis indicates the experiment number

### 5.5.7 Effect of the number of jobs in the overlapping region on savings from carrier collaboration

The effect of the number of jobs in the overlapping region on savings from carrier collaboration is studied in analysis 7 and the results are shown in **Table 5.8** which is organized as follows. In column 1, the description of the value is provided whether it is the average percentage of savings, minimum value, or maximum value. Columns 2 through 3 show the average percentage of savings obtained from the 3 experiments with the different proportions of jobs in the overlapping region. It should be noted that the percentage of savings increases as the number of jobs in the overlapping region increases. The increase in savings for every three additional jobs in the overlapping region is between 0.4% and 1.8%, even when 50% of the jobs are retained by each carrier.

**Table 5.8 Changes in the percentage of savings with the proportion of jobs in the overlapping region**

| | The proportion of jobs from exclusive and overlapping region | | |
|---|---|---|---|
| | **(18, 12)* (#55)**** | **(21,9) * (#60)**** | **(24,6) * (#61)**** |
| **Average savings (%)** | 17.2 | 15.4 | 15.0 |
| **Min (%)** | 7.6 | 10.9 | 9.9 |
| **Max (%)** | 24.8 | 20.7 | 21.0 |

* (number of jobs in the exclusive carrier region, number of jobs in the overlapping region), ** The number in the parenthesis indicates the experiment number.

# CHAPTER 6
# Summary and Conclusions

The main objective of this research project was to improve the efficiency of the freight transportation system in South Carolina. A two-stage model was developed to take advantage of intermodal transportation for long hauls and collaboration among LTL carriers to improve regional pickup and deliveries over short distances. Intermodal facility locations are strategic decisions and long term, which were modeled using a multi-period approach. The job-sharing decisions in carrier collaboration are operational and short term, which were modeled using a single period approach. It is thus evident that the two above-mentioned processes (strategic and operational decision making) are physically separated in the real world. Both the models together provide an integrated tool to develop a network that utilizes intermodal transportation for long hauls and LTL carrier collaboration for regional pickup and deliveries.

For strategic planning, a multi-period MILP model (IMTLP) was developed to design an intermodal freight network over a planning horizon. The model considered the product volumes, modes, budget, and short-term inventory at the IMTs. To resemble the real-world scenarios, the concept of specific demands and total demands is introduced which allows a consignee to demand freight from a specific shipper or any shipper. Using the developed model, numerical experiments were performed on a flexible network that was developed for a given budget and availability of modes by dividing a planning horizon into multiple time periods and considering the pre-forecasted costs, mode availabilities, and demands for time periods. For operational planning, a MILP model (CCVRPPD) was developed to optimally allocate the shared jobs to the carriers by finding optimal vehicle routes to serve all jobs (both shared and retained). To solve the large problem instances, a solution methodology based on the LNS heuristic was developed. A new insertion algorithm based on greedy heuristic was proposed for the LNS heuristic. Using the developed model and solution method, numerical experiments were performed on hypothetical networks that examine the variation of cost savings under different collaboration scenarios.

The experimental results from the strategic model (IMTLP) show the importance of Columbia's location as an IMT. When no IMT can be opened, all the demands are satisfied through direct shipping and the total network cost is 81% greater than the base case. The regions with higher supply or demand of freight volume tend to have higher utilized IMTs and impact the total network cost most. The model supports a decision-maker exploring the impact of incrementally adding IMTs. IMTs opened first near the shipper/consignees having a higher freight volume to be shipped or received. The sensitivity analysis for budget shows that intermodal shipping share and total network cost converge at some point and the model does not add any new IMTs to improve the network performance. The alternate optimal solutions for the number of IMTs in an intermodal network show how we can tradeoff intermodal shipping share and total network cost with budget investment in opening IMTs. The experimental results from the operational model (CCVRPPD) indicated that carrier collaboration can yield significant savings and revealed several important insights as provided below. The cost savings from the collaboration is dependent on the spatial distribution of the nodes in the network. That is, two networks with the same number of nodes will not necessarily yield the same cost savings. The distance between the carriers' depots was found to affect cost savings. The farther apart they are, the higher the cost savings. As is the case with economies of scale, collaboration is more beneficial when the combined logistics network is larger. Similarly, economies of scale apply to the number of pooled jobs; that is, the greater the number of pooled jobs, the greater the cost savings. The cost savings, when carriers are allowed to retain some of their jobs is smaller than that when carriers pool all jobs, but it is higher than that of non-collaboration. Therefore, allowing carriers to retain some jobs is beneficial as it encourages collaboration participation. Although cost savings increase with the size of the overlapping region, having a smaller region with a higher number of pooled jobs is more beneficial than having a larger region with a fewer number of pooled jobs. However, the increase in cost savings for the pooled jobs and size of the overlapping region is non-linear; significant benefits can be achieved through relatively small collaboration efforts by the carriers.

There is some clear direction for future research: (1) the current model structure for the strategic model (IMTLP) could be expanded to make the results more useful for the decision-maker. For example, allowing IMTs that have already been opened to have a capacity expansion rather than opening a new IMT is certainly a realistic extension. Also, all IMTs in this model are assumed to be the same (i.e., size, capacity, available modes); however, future research should also consider alternatives at the locations including IMT's that support rail-rail, rail-road, and rail-marine, (2) allowing key parameters to reflect the uncertainties seen in practice. The current strategic model (IMTLP) assumes that many key factors like costs, demands, supplies, and mode availabilities are known with certainly a priori. Relaxing this assumption on some of the inputs and developing a stochastic model that reflects stochasticity in some parameters would add significant value to the model and results, (3) the operational model (CCVRPPD) does not address the benefit of the individual carrier or profit allocation; this can be achieved either by post-optimization profit allocation or adding minimum profit thresholds into the integrated model for each carrier. Thus, the future work will explore strategies to share profits among participating carriers in the alliance to promote collaboration. (4) The operational model (CCVRPPD) has the following assumptions which can be relaxed in future research to make the model realistic: the operation is either pickup or delivery for each customer location, the service time at each customer location is zero, and each carrier has only one depot.

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