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Design and Analysis of Efficient Freight Transportation Networks in a Collaborative Logistics Environment

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by
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Abstract

The increase in total freight volumes, reducing volume per freight unit, and delivery deadlines has increased the burden on freight transportation systems of today. With the evolution of freight demand trends, there also needs to be a evolution in the freight distribution processes. Today's freight transportation processes have a lot of inefficiencies which could be streamlined, thus preventing concerns like increased operational costs, road congestion and environmental degradation. Collaborative logistics is one of the approaches where supply chain partners collaborate horizontally or/and vertically to create a centralized network which is more efficient and serving towards a common goal or objective. In this dissertation, we study intermodal transportation, and cross-docking, two major pillars of efficient, cheap and faster freight transportation in a collaborative environment. We design an intermodal network from a centralized network perspective where all the participants intermodal operators, shippers, carriers and customers strive towards a synchronized and cost efficient freight network. Also, a cross-dock scheduling problem is presented for competitive shippers using a centralized cross-dock facility. The problem studies the impact of real time information transfer between the shippers and cross dock facility, in case of changing arrival times of inbound trailers.

Firstly, we present a capacitated Intermodal Terminal Location Problem (IMTLP). The shippers must meet the demands of the customers either through intermodal shipping or direct shipping. The intermodal shipping is in form of standardized containers from point A to point B without goods repacking in between, and change of modes only allowed at intermodal terminals (IMTs). Such a containerized transportation eliminates extra material handling costs needed for repacking of freight. Multiple shippers may used trucks to direct ship freight to an intermodal terminal and use it as a consolidation facility, from where consolidated freight is carried to the other intermodal terminal using one of the mode choices available like rail, barge, or air, and then again

use trucks to direct ship freight to the end customers. Intermodal shipping is more suitable for longer hauls and large volumes of freight shipments due to economies of scale, whereas direct shipping is more suitable for shorter hauls, and lower volumes of freight shipments as it eliminates extra material handling costs for change of modes at intermodal terminals. The strategic decision of selecting the location of these intermodal terminals is a complex and critical decision, and if not optimized may lead to irreversible losses due to under or over-utilization of intermodal terminals. We study this complex problem with elements like multi-product, multi-mode, and short-term inventory at IMTs in a multi-period setting.

Next, we extend the capacitated IMTLP and study the problem under facility disruptions. These disruptions may occur at shipping facilities or/and intermodal terminals and lead to disruption in facility operations. The disruption duration and locations impacted are uncertain, and lead to uncertainty in supply at shippers and throughput/material handling capacity at intermodal terminals. A two-stage stochastic model is developed, where the first stage decisions are strategic decisions of intermodal facility locations, and the second stage/recourse decisions are operational decisions regarding freight distribution in a disruption scenario. We solve this problem for a finite number of scenarios and a given discrete probability distribution. Since, this is a complex problem in terms of computational time, decomposition techniques are applied and then enhanced using regularization techniques. We also present two case studies for the state of South Carolina for both the studies mentioned above.

Finally, we study the cross-dock scheduling problem for a multi-door facility. Cross-docks are a transshipment facility used in logistics for consolidation of freight by destination. In this study we tackle the truck scheduling problem at a cross-dock under scattered inbound trailer arrival times to minimize tardiness of outbound trailers and make-span. A mixed-integer programming model is developed for the problem which includes features like soft departure deadlines, scattered inbound trailer arrivals, multiple dock doors, non-linear penalty for tardiness and product interchangeability. Inbound trailer arrivals and outbound trailer departures must be synchronized to reduce inventory and ensure faster trans-shipments. This problem is well known to be NP-hard, and thus is challenging to solve using commercial solvers under a computation time acceptable for real-time applications. We develop a constructive heuristic, Multi-door Cross-dock Heuristic (MDCDH), to produce good quality starting solutions and then use population based simulated annealing (PBSA) meta-heuristic to improve the solution quality. Also we provide key insights for design and operations of cross-dock from cross-dock and carrier perspective. The developed methodology can be extended to be applied to an online cross-dock scheduling problem with uncertain inbound trailer arrival times. The real-time information exchange between cross-dock and freight carriers under uncertainties can lead to an efficient cross-docking process. The change in arrival times when reported to cross-docks can be utilized to re-optimize the scheduling and update the carriers about the new schedule.

Dedication

This dissertation is dedicated to my loving family, my father Om Parkash Badyal, mother Asha Badyal, sister Poonam Mundepi and dear friend Aishwarya Srivastava who always put their trust in me, supported me through tough times and motivated me through the challenges.

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I am thankful to the committee members Dr. Mary E. Kurz, Dr Scott J. Mason, and Dr. Yongjia Song for providing valuable insights and guidance. They were immensely helpful whenever my research was stuck and without their contributions and feedback this dissertation would not have been any better.

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Chapter 1

Introduction

The majority of freight in the United States is shipped using highways, followed by air, railroads and waterways. The transportation system contributed a total of approx. 6% towards the U.S. Gross Domestic Produce (GDP) in the year 2018 [3]. Figure 1.2 shows the routes of these freight flows and the volume of freight carried is represented by the thickness of the route.

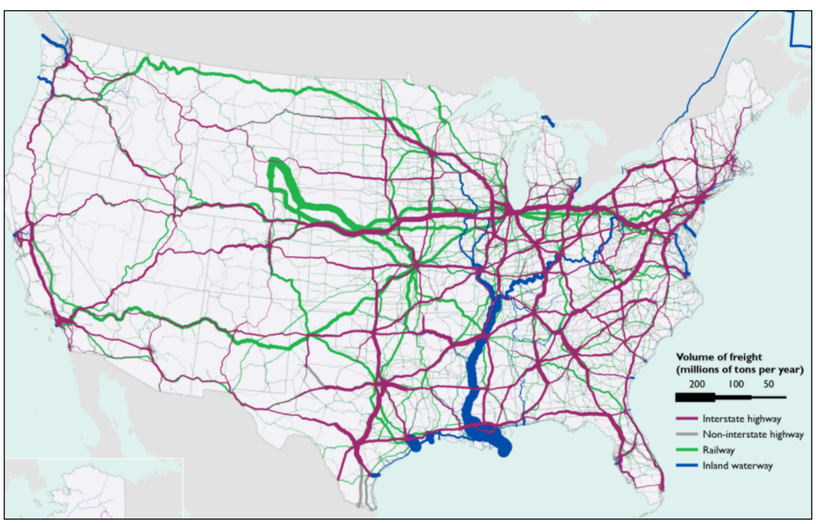


Figure 1.1: Freight flows for the year 2018 (except highways-2015) classified by modal choice. (Source: Transportation Statistics Annual Report, 2020, U.S. D.O.T.)

The rise of globalization, e-commerce, freight demands, in-house transportation, and fast deliveries are some of the factors that are contributing towards increasing freight flows and a change in trend of freight flows. There was an increase of 2000% in e-commerce sales between the years

2000 and 2019, and a 4% increase in tons of freight per capita moved between the years 2016 and 2018 [3]. As shown in Figure 1.2 in 2018, trucks carried the highest share of freight by value at 60.9%, followed by air, rail, and water. The increase in freight flows is leading to increased burden on truck transportation and thus highways, leading to problems like road congestion, environmental degradation, and increased trucking costs.

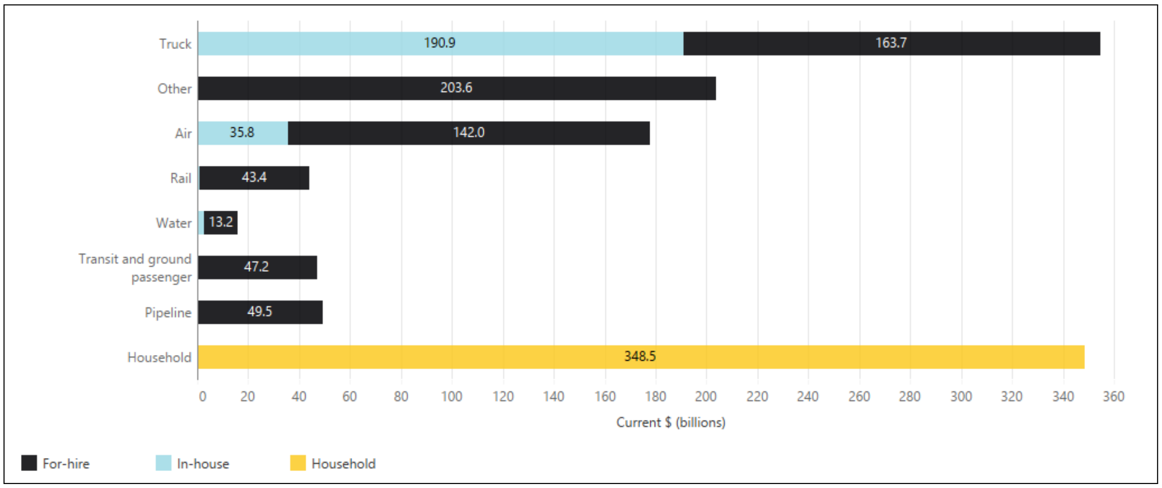
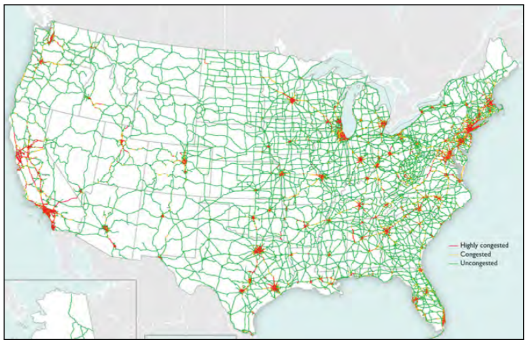


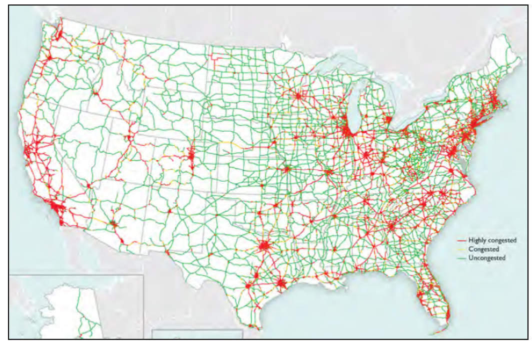
Figure 1.2: GDP Contribution classified by type of transportation mode. (Source: U.S. DOT, Bureau of Transportation Statistics)

According to the Bureau of Transportation Statistics (BTS), "Long-haul freight truck traffic on the National Highway System is projected to increase dramatically. Projected data indicate that truck travel may increase from 311 million miles per day in 2015 to 488 million miles per day by 2045." It also reports that the congestion during peak periods on National Highway System (NHS) is going to increase on high-volume truck routes. Figure 1.3a shows the peak period congestion in 2015 whereas Figure 1.3b shows the projected peak-period congestion in 2045. The red areas represent highly congested, yellow areas represent congested and green regions represent uncongested highways.

There is a need to tackle these future logistic challenges using more sustainable freight transportation practices and collaborations among supply chain partners. Modal shifting from trucks to more environment friendly modes like rail and water for long-hauls can be cheaper due to economies of scale. Freight consolidation promotes Full-truckload (FTL) shipping, thus utilizing maximum capacity of modes and avoids wasted capacity as compared to LTL shipping. Also, Collaborative Logistic Networks (CLNs) utilize cooperation between supply chain partners at horizontal and vertical levels to promote a more centralized and overall more efficient network than the decentralized counterparts.



(a) Peak N.H.S. Congestion, 2015



(b) Projected Peak N.H.S. Congestion, 2045

Figure 1.3: US National Highway System Peak Period Congestion. (Source: Transportation Statistics Annual Report, 2020, U.S. DOT)

According to Ferrell et al. [35], “Collaborative logistics describes the practice where companies work together to improve efficiency in their supply chains rather than operate in isolation and accept the inefficiencies that frequently results.” Horizontal collaboration is cooperation or information exchange among the competing organizations working on same level of supply chain to optimize their combined processes. Vertical collaboration is cooperation or information exchange between organizations at different level of supply chains (e.g. shipper, carrier, retailers) to achieve a common objective of a centralized, fast, more streamlined, and cost efficient supply chain. Horizontal collaboration is less prevalent due to concerns of information sharing with competitors.However, if applied successfully through a centralized agency which maintains integrity of important information and distributes profits through a agreeable profit sharing policy can lead to a win-win situation for all the participating competitors.

In this dissertation, we study two efficient freight distribution practices, intermodal transportation and cross-docking in a collaborative logistics environment. These freight networks are designed utilizing vertical and horizontal collaboration among various acting supply chain partners.

Intermodal transportation can be defined as the movement of goods from an origin to a destination using at least two modes of transportation. In this dissertation, the focus is limited to the network where goods are not repacked and transfer of loads (typically in containers) takes place only at intermodal terminals (IMTs). Intermodal network is a big complex network and has various participants like shippers, carriers, intermodal operators, retail/end-customers. The network is designed for horizontal collaboration among shippers, and carriers, and vertical collaboration among shippers, carriers, intermodal operators, and end-customers. Intermodal networks utilize intermodal terminals as consolidation centers for all incoming shipments from shippers through carriers, use appropriate mode like rail, air, or barge for long-haul shipment to other intermodal terminals, and finally freight is unconsolidated to be shipped through carriers to the end-customers.

Cross-docking is a consolidation process, where inbound shipments from multiple shipper destined to multiple end-customers are received, sorted and consolidated by destinations to be dispatched in FTL outbound trailers to the end-customers. A generic example of cross-dock layout and operations is represented by Figure 1.4. There might be no or a short period of storage (<24h) at cross-dock, thus leading to fast deliveries, and reduced inventory costs. Cross-dock scheduling is studied from a prospective of horizontal collaboration among shippers, and vertical collaboration among carriers and cross-dock operator. Shippers ship freight through carriers to cross-dock for consolidation and utilize FTL shipping, which minimizes unutilized capacity in shipping vehicles.

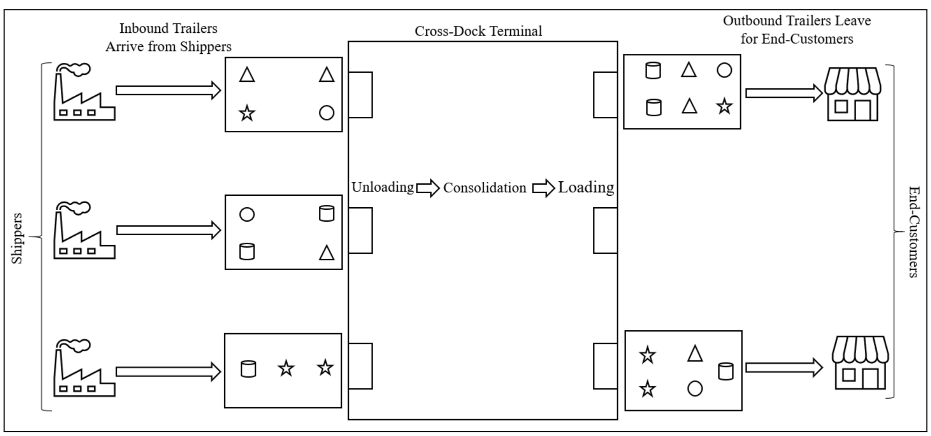


Figure 1.4: An example of layout and operations at a Cross-Dock terminal

In chapter 2, we present a multi-period optimization model for citing intermodal terminals in a network which also supports direct shipping. The study also adds an element of short-term inventory at intermodal terminals to facilitate freight consolidation, and also satisfy periods with demands in excess of available supply. The problem is studied for real world application and thus includes important aspects like budget for opening intermodal terminals, and multiple-products.

In chapter 3, we study the intermodal network under facility disruptions at shippers and intermodal terminals. The disruptions impact the operation of the facilities leading to reduced supply available and intermodal terminal throughput/material handling capacity. The disruption duration and impacted locations are uncertain. Finite number of disruption scenarios with available discrete probability are assumed to be available. We also develop a case study for hurricane disruptions in state of South Carolina using public data sets. The results show long-term benefits of using stochastic model as compared to a deterministic model.

In chapter 4, we study a cross-dock scheduling problem with asynchronous arrival times of inbound trailers. The post-distribution concept is also added as a feature to allow for better utilization for trailer capacities. Under product distribution products are interchangeable and products needed by an outbound trailer can be provided by any inbound trailer with available supply. The study also develops computationally fast heuristic and meta-heuristic to provide quality solutions. This allows the methodology to be applied to a real-time or online application. Also we develop some operational and design insights for cross-docks and freight carriers. For future research the information exchange (inbound trailer arrival times and updated schedules) between cross-dock and inbound carriers would allow us to re-optimize our scheduling in case of change in inbound trailer arrival times.

Chapter 2

A Multi-Period Optimization Model for Siting Capacitated Intermodal Facilities

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2.1 Introduction

The US freight transportation system moved nearly 17 billion tons of freight in 2012, 17.7 billion tons in 2016 and is expected to have a demand for 25.5 billion tons in 2045 [2]. This growth in freight movement will exacerbate the problems of road congestion, air pollution, and noise pollution. Freight Analysis Framework projects the multiple mode freight transportation to double from 1.3 billion tons in 2016 to nearly 3.0 billion tons in 2045 [2]. Globalization of the trade market is leading to increased imports and exports. US-international freight value increased from $2.4 trillion in 2000 to $3.2 trillion in 2016 [2]. There is a need to develop strategies that meet the increasing demands efficiently while tackling these challenges.

Intermodal transportation can be defined as the movement of goods from an origin to a destination using at least two modes of transportation. In this research, the focus is limited to the network where goods are not repacked and transfer of loads (typically in containers) takes place only at intermodal terminals (IMTs). Intermodal transportation creates a synchronization between more expensive, fast, and flexible modes of transport and less expensive, slower, and less flexible modes of transport [42]. The US government has been encouraging the use of intermodal transport by creating legislation such as the Intermodal Surface Transportation Efficiency Act of 1991(ISTEA '91) and the Transportation Equity Act for the 21st Century (TEA-21). However, trucks still carry 62.7% of the weight and 61.9% of the value of all goods shipped in the United States and is the predominant mode for shipments under 750 miles [2]. The large number of trucks on highways lead to the negative externalities mentioned earlier, as well as the inability of the freight network to cope when there is a disruption.

Appropriate use of properly located intermodal terminals can significantly increase the usage of the intermodal transport [70]. Opening an intermodal facility involves an initial setup cost, operational costs, material handling costs, etc. If a terminal's location does not attract enough freight throughout the planning horizon it may become very expensive to operate. Also, an incorrect number of terminals may leave the network underutilized or overloaded. Groothedde et al. [42] considers 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 Intermodal Terminal Location Problem (IMTLP). Costs, capacities, and demands are all dynamic in nature. Multi-period planning provides the opportunity to systematically invest capital over the multiple time 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 [39] the multi-period approach benefits the stakeholder as: (i) it reduces the burden financially to expand network over a short period of time, (ii) it helps in managing resources better by opening IMTs "just-in-time", and (iii) it improves the routing decisions for different time 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.

One unique aspect of this research is that a limited amount of freight can be held at IMTs as "inventory". One reason is to facilitate load consolidation. This can be quite effective at improving the utilization of transportation assets [34]. Another reason is that shippers could use the IMTs as storage for inventory that would be needed to satisfy demand in a future period that exceeds their short-term supply capacity. Hence, the research includes an area in the IMT where some freight can be held for a limited duration. Two important parameters associated with holding inventory are the maximum amount of freight that can be held in an IMT and the maximum length of time it can remain in the IMT. Both of these are model inputs in this research; and both could be varied to explore their impact on system cost and efficiency. This research assumes the maximum length of time freight can remain in the IMT to be unconstrained for all the experiments.

The objective of this research is to locate IMTs in the network to minimize cost. A mixed-integer linear program has been developed to accomplish this objective. The dynamic nature is embedded by having the model determine the choice of transportation mode between the IMTs and allow inventory to be held at IMTs. A series of experiments are performed to design and analyze the intermodal network for the state of South Carolina using the Freight Analysis Framework Version 4.5 (FAF^4), 2017 dataset. The contribution of this research is the development of a multi-period model to assist planners in locating IMTs that includes new and important elements like multiple products that can be consolidated at the IMTs, the ability to hold inventory at the IMTs, as well as traditional notions of budget, capacities (e.g., transportation mode and IMT), and demand. The potential practical value of the model is then illustrated by using it to identify the optimal intermodal freight network based on real data from South Carolina.

2.2 Literature Review

The literature on facility location is extensive so this review focused on that which is most relevant to intermodal transportation and the nature of this research. According to Teye et al. [72] Intermodal Terminal Location Problems (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 [60, 59, 61]. Later, a multiple allocation model based on linear integer programming was developed by Campbell [26]. 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 opening of IMTs and variable costs for unimodal and intermodal transportation [12, 13]. 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. [46] 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 time service constraints. A tabu search metaheuristic was used to obtain solutions for large-sized problems. Meng et al. [55] 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. [7] developed a linear mixed-integer linear programming (MILP) model that jointly considered transportation costs and travel times; and was solved using a heuristic.

Sorensen et al. [70] adapted the original model presented in Arnold et al. [12] to develop a bi-objective problem considering the 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. [66] 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. [72] formulated a non-linear mixed-integer programming model. The model solves the facility location problem but also gives the shippers a choice of whether to use an IMT or not.

Ghane-Ezabadi et al. [40] 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. [4] 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 research that has been discussed is single period. Including multiple periods 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 [25] that involved a continuous variable approximation model for hub location with demand growing over time. Contreras et al. [29] 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. [8] 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. [8] 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. [30] proposed a stochastic model for hub location with uncertain demands and transportation costs. Fotuhi et al. [37] proposed a stochastic model for competitive IMT location problem with uncertain demands. In our study, we consider the demands to be forecasted beforehand and thus model is deterministic in nature. We assume that the IMTs can hold inventory over a few time periods. A similar approach was used by Bhattacharya et al. [18] but not in a multi-period setting.

Table 2.1: Comparison between different relevant studies based on literature review

Reference	Objective[1]	Modelling approach[2]	Multi-Period	Budget constraint	Inventory at IMTs	Volume Considered	Uncertainty in Parameters
Ishfaq et al. 2011	CM	MIP	X	X	X	X	X
Contreras et al. 2011a	CM	MIP	✓	X	X	X	X
Contreras et al 2011b	CM	MIP	X	X	X	X	✓
Alumur et al. 2012	CM	MIP	X	X	X	X	X
Sorenson et al. 2013	CM	Bi-objective MIP	X	X	X	X	X
Bhattacharya et al. 2014	CM	MIP	✓	X	✓	X	X
Fotuhi et al. 2015	–	MINLP	X	X	X	X	✓
Alumur et al. 2016	CM	MIP	✓	X	X	X	X
Ghane-Ezabadi et al. 2016	CM	IP	X	X	X	X	X
Abbassi et al. 2019	CM	MIP	X	X	X	X	✓
Current Research	CM	MIP	✓	✓	✓	✓	X

[1] CM: Cost Minimization

[2] MIP : Mixed Integer Programming, MINLP: Mixed Integer Non-Linear Programming, IP: Integer Programming

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 here includes multiple product types and the opportunity for inventory to be held in 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 capacity. By including these types of features, the model can be used to explore the impact of the amount of IMT space dedicated to holding inventory on network efficiency. Hence, this model if fundamentally different from existing models in the literature on IMTLP and can be used to provide decision more insight into designing IMT networks to support vertical and horizontal collaboration.

2.3 Methodology

2.3.1 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 customers to the IMT and form 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) intermodally from shipper to customer via a pair of IMTs, (3) shipper to the customer through a single IMT. The sum of the latter two flow types together is considered as intermodal shipping. This model builds 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 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 single budget allocated for IMT opening for the entire planning horizon that cannot be exceeded. The IMTs can hold inventory, but unloading, holding, and loading costs are incurred depending on the product type. The consignees can demand a specific freight type from a specific shipper, or they can simply have their demand for that product satisfied from any shipper via any freight type. Henceforth, the former will be referred to as “specific demand” and the latter “free demand”.

The remaining key assumption behind this model are: (i) The goods transfer between the non-hub nodes and hub-nodes are done by trucks only, (ii) IMTs have an inventory holding capacity.

In this study the authors propose a multiple-allocation capacitated mixed-integer linear programming model. The decisions that the model makes are: (i) locating the intermodal terminals, (ii) routing the freight, (iii) selecting the transportation mode between IMTs, and (iv) deciding the amount of inventory to hold at 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 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 time periods of equal or unequal duration.

2.3.2 Mathematical Formulation

This section describes the mathematical programming model and notation.

2.3.2.1 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^t_{ijm}	fixed cost for operating a terminal link using mode m between IMTs $i \in H$ and $j \in H$ for period $t \in T$
CI^t_{ijmp}	per unit transportation cost for product p from IMT $i \in H$ to IMT $j \in H$ using mode $m \in M$ for period $t \in T$
CP^t_{kip}	per unit drayage cost for product $p \in P$ from shipper $k \in N$ to IMT $i \in H$ using road transport for period $t \in T$
CE^t_{jgp}	per unit drayage cost for product $p \in P$ from IMT $j \in H$ to receiver $g \in N$ using road transport for period $t \in T$
CU^t_{ip}	per unit unloading cost for product $p \in P$ at IMT $i \in H$ for period $t \in T$

CL_{ip}^{t} per unit loading cost for product p ∈ P at IMT i ∈ H for period t ∈ T

CH_{ip}^{t} per unit holding cost for product p ∈ P at IMT i ∈ H for period t ∈ T

CD_{kgp}^{t} per unit direct shipping cost for product p ∈ P between shipper k ∈ N and receiver g ∈ N for period t ∈ T

D_{gkp}^{t} demand for product p ∈ P belonging to shipper k ∈ N at receiver g ∈ N for period t ∈ T

DT_{gp}^{t} total demand for product p ∈ P at receiver g ∈ N for period t ∈ T

S_{kp}^{t} supply available at shipper k ∈ N for period t ∈ T

VP_{p} per unit volume of product p ∈ P

VM_{m} volume capacity of mode m ∈ M

VT volume capacity of a truck

TI_{ijm}^{t} maximum number of trips available between IMTs i ∈ H and j ∈ H for a mode m ∈ M in period t ∈ T

TP_{ki}^{t} maximum number of pre-haul trips available between shipper k ∈ N and IMT i ∈ H in period t ∈ T

TE_{jg}^{t} maximum number of end-haul trips available between IMT j ∈ H and receiver g ∈ N in period t ∈ T

TD_{kg}^{t} maximum number of direct shipping trips available between shipper k ∈ N and receiver g ∈ N in period t ∈ T

C_{i}^{t} material handling capacity of IMT i ∈ H in period t ∈ T

HC_{i}^{t} inventory holding capacity of IMT i ∈ H in period t ∈ T

B budget for opening IMTs for the entire planning horizon

Decision variables

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

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

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

x_{ijmkp}^t number of units of products p $\in$ P belonging to shipper k $\in$ N shipped from IMT i $\in$ H to IMT j $\in$ H using mode m $\in$ M

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 for 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

2.3.2.2 Mathematical Model

The proposed Mixed Integer Linear Programming model is presented below,

Minimize,

$$\begin{aligned} &\sum_{i\in H} F_i\xi_i + \sum_{i\in H}\sum_{j\in H}\sum_{m\in M}\sum_{t\in T} f_{ijm}^t z_{ijm}^t + \sum_{i\in H}\sum_{j\in H}\sum_{m\in M}\sum_{k\in N}\sum_{p\in P}\sum_{t\in T} CI_{ijmp}^t x_{ijmkp}^t \\ &+ \sum_{k\in N}\sum_{i\in H}\sum_{p\in P}\sum_{t\in T} CP_{kip}^t q_{kip}^t + \sum_{j\in H}\sum_{g\in N}\sum_{k\in N}\sum_{p\in P}\sum_{t\in T} CE_{jgp}^t r_{jgkp}^t + \sum_{i\in H}\sum_{k\in N}\sum_{p\in P}\sum_{t\in T} CU_{ip}^t u_{ikp}^t \\ &+ \sum_{i\in H}\sum_{k\in N}\sum_{p\in P}\sum_{t\in T} CL_{ip}^t l_{ikp}^t + \sum_{i\in H}\sum_{k\in N}\sum_{p\in P}\sum_{t\in T} CH_{ip}^t h_{ikp}^t + \sum_{k\in H}\sum_{g\in N}\sum_{p\in P}\sum_{t\in T} CD_{kgp}^t h_{kgp}^t \end{aligned} \tag{2.1}$$

Subject to,

$$\sum_{\substack{j\in H\\ j\neq i}}\sum_{m\in M} x^t_{jimkp} + \sum_{k\in N} q^t_{kip} + l^t_{ikp} = \sum_{m\in M}\sum_{j\in H} x^t_{ijmkp} + \sum_{\substack{j\in H\\ j\neq i}}\sum_{g\in N} r^t_{jgkp} + u^t_{ikp},$$
$$\forall i\in H, k\in N, p\in P, t\in T, \tag{2.2}$$

$$h^t_{ikp} = h^{t-1}_{ikp} + u^t_{ikp} - l^t_{ikp}, \qquad \forall i\in H, k\in N, p\in P, t\in T \tag{2.3}$$

$$w^t_{kgp} + \sum_{j\in H} r^t_{jgkp} \geq D^t_{gkp}, \qquad \forall g,k\in N : g\neq k, p\in P, t\in T \tag{2.4}$$

$$\sum_{k\in N} w^t_{kgp} + \sum_{k\in N}\sum_{j\in H} r^t_{jgkp} \geq DT^t_{gp}, \qquad \forall g\in N, p\in P, t\in T \tag{2.5}$$

$$\sum_{i\in H} q^t_{kip} + \sum_{\substack{g\in N\\ g\neq k}} w^t_{kgp} \leq S^t_{kp}, \qquad \forall k\in N, p\in P, t\in T \tag{2.6}$$

$$\sum_{k\in N}\sum_{p\in P} x^t_{ijmkp} VP_p \leq TI^t_{ijm} V_m z^t_{ijm}, \qquad \forall i,j\in H : i\neq j, m\in M, t\in T \tag{2.7}$$

$$\sum_{p\in P} q^t_{kip} VP_p \leq TP^t_{ki} V_t y^t_i, \qquad \forall k\in N, i\in H, t\in T \tag{2.8}$$

$$\sum_{k\in N}\sum_{p\in P} r^t_{jgkp} VP_p \leq TE^t_{jg} V_t y^t_j, \qquad \forall g\in N, j\in H, t\in T \tag{2.9}$$

$$\sum_{p\in P} w^t_{kgp} VP_p \leq TD^t_{kg} V_t, \qquad \forall g\in N, j\in H, t\in T \tag{2.10}$$

$$\sum_{\substack{j\in H,\\ j\neq i}}\sum_{m\in M}\sum_{k\in N}\sum_{p\in P}x^t_{ijmkp}+\sum_{\substack{j\in H,\\ j\neq i}}\sum_{m\in M}\sum_{k\in N}\sum_{p\in P}x^t_{jimkp}\leq C^t_i,\qquad \forall i\in H,t\in T \tag{2.11}$$

$$\sum_{i\in H}F_i\xi_i\leq B \tag{2.12}$$

$$\sum_{k\in N}\sum_{p\in P}h^t_{ikp}\leq HC^t_i\qquad \forall i\in H,t\in T \tag{2.13}$$

$$z^t_{ijm}\leq y^t_i,\qquad \forall i,j\in H:i\neq j,m\in M,t\in T \tag{2.14}$$

$$z^t_{ijm}\leq y^t_j,\qquad \forall i,j\in H:i\neq j,m\in M,t\in T \tag{2.15}$$

$$y^t_i\geq y^{t-1}_i,\qquad \forall i\in H \tag{2.16}$$

$$M\xi_i\geq\sum_{t\in T}y^t_i,\qquad \forall i\in H \tag{2.17}$$

$$z^t_{ijm},y^t_i,\xi_i\in\{0,1\}\qquad \forall i,j\in H:i\neq j,m\in M,t\in T \tag{2.18}$$

$$\begin{aligned}&q^t_{kip},x^t_{ijmkp},r^t_{jgkp},w^t_{kgp},u^t_{ik},l^t_{ik},h^t_{ik}\geq 0\text{ and Integers}\\&\forall k,g\in N:k\neq g,i,j\in H:i\neq j,m\in M,p\in P,t\in T\end{aligned} \tag{2.19}$$

The objective function (1) minimizes the total relevant network cost which includes the fixed cost of opening an IMT, fixed cost for using an intermodal link, cost of shipping between IMTs, cost of pre-hauls, cost of end-hauls, unloading cost, loading cost, holding cost at IMTs, and cost of direct shipping. Constraints (2) are the flow balance constraints at IMTs. They also track the number of loaded and unloaded units. Constraints (3) are the multi-period inventory constraints that also balance inventory 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) limits 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 'ξ_i'. Constraints (18, 19) define the variable types.

2.4 Results and Discussion

2.4.1 South Carolina Case Study

The model is now used in a case study based on South Carolina data. The State is divided into five zones that are developed from regional map divisions, FAF Zones. There are 26 total nodes in the case study network with 13 representing the freight supply and demands as illustrated in Figure 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 1b. They were located at major road and rail intersections across the State and at 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 time periods.

In the model, consolidation centers are assumed to be located at single points in each region.

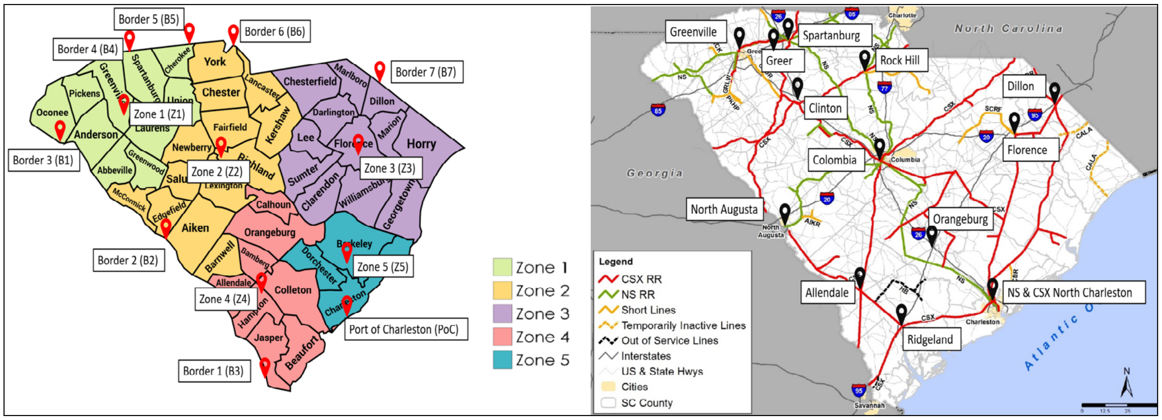


Figure 2.1: (a)The map shows 13 customer nodes, the five zones, and (b) the map shows the 13 potential IMT locations (Source 1(b): South Carolina Statewide Freight Plan, 2017, SCDOT, [1])

These are determined by minimizing the total distance between the consolidation center location and the mean population centers of each county in the zone (23). The FAF4 Origin-Destination Data (24) for South Carolina FAF zones (Figure 2.1a) 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, 2017 for freight origins and, (ii) annual estimates of resident population, 2017 for freight destinations - as proportional weights to the specific zones (25). The Standard Classification of Transported Goods (SCTG) - North American Industry Classification System (NAICS) cross-reference (26) 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 node, 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 illustrated in Table 2 and Table 3.

Table 2.2: Data used for the model parameters

Parameters	Range/Values						
	Basic Chemicals	Coal	Coal-n.e.c.	Gravel	Mixed Freight	Natural Sands	Waste/Scrap
Specific Volume (ft^3/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 ($\$/ton$)	100-200	200-250	100-200	100-200	500-1000	100-200	1000-2000

Table 2.3: Data used for the model parameters

Parameters	Range/Values
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 2, the specific volume of the 2-digit STCG products is deterministic and is computed by using the average densities of the constituting products. Additional volume specific to the commodity type is added to account for packing inefficiencies. In Table 3, 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 (27). 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 (28) 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 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 grey part represents freight volume received by a consignee. The green circles represent freight volume handled by IMTs. The highest intermodal freight handled is most by Columbia at 26% followed by Florence at 19%. Highest overall intermodal share was for coal at 99% followed by coal-n.e.c.at 92% as most of the freight enters from border points and is destined for longer distance hauls to Port of Charleston. Lowest overall intermodal share was for waste/scrap at 30%, followed by Gravel at 38% as most of the freight flow for these product types had the same origin as the destination (demand within a zone).

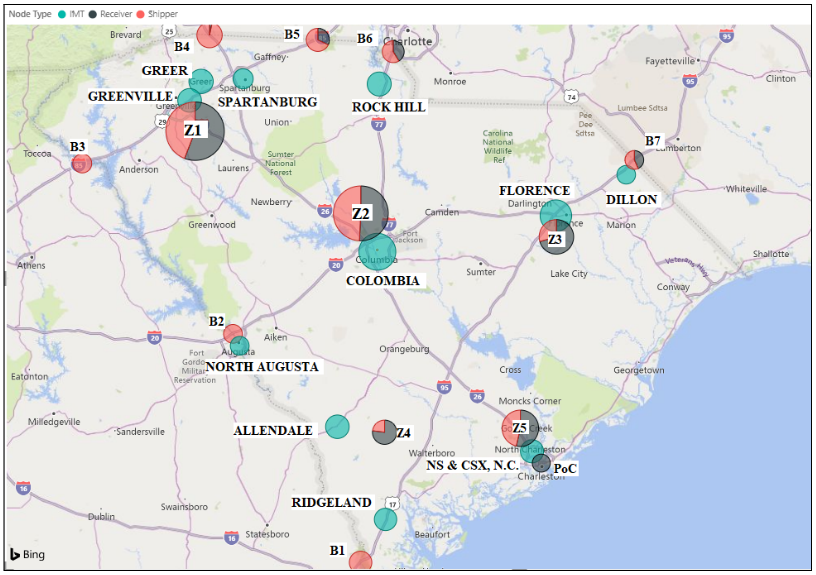


Figure 2.2: Freight volume at shippers, consignees and IMTs summed over all the time periods for the case study (only IMTs opened are shown)

The results show that an IMT in Columbia is quite important. When the Columbia IMT is removed and the model 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%, intermodal shipping share decreases by 16%, and the average direct shipping distance increases by 39%. Clearly, Columbia 's location near the geographic center of the State is critical to system performance when the budget is unlimited.

2.4.2 Sensitivity Analysis

2.4.2.1 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 a budget so one can get significant improvement with much less investment than might be expected. The second is to see which IMT 's are opened as the budget is increased. Does an increasing budget simply add additional IMT 's or, at some point, do a completely different set represent the optimal solution?

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 obtained.

Table 2.4: 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 3 and show interesting spatial results pertaining 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 money allows the freight in the east to be more efficiently handled by two IMT's located towards the north and south rather than on in the middle.

Figure 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 more than doubles the amount of freight shipped intermodally. The associated total network cost reduction is 22.5% and while this is nice and important, the number of trucks that are removed from the roadways could be a significant result with positive implications that extend far beyond this model and highly important to requesting increased budgets. Further increasing the budget from 50% of the base budget to 75% yields a saving of 21.8% in total network cost, but just 6.7% savings when the budget is increased from 75% to 100%. The savings increase even more steeply on further increase in budget, 0.93% from 150% to 175% and 0.99% from 175% to 200%. This reveals the nonlinear trend in total network cost when the budget is varied. This has a major impact on decision-makers as it becomes important to identify the budget after which further investment leads to a diminishing increase in savings which are unacceptable.

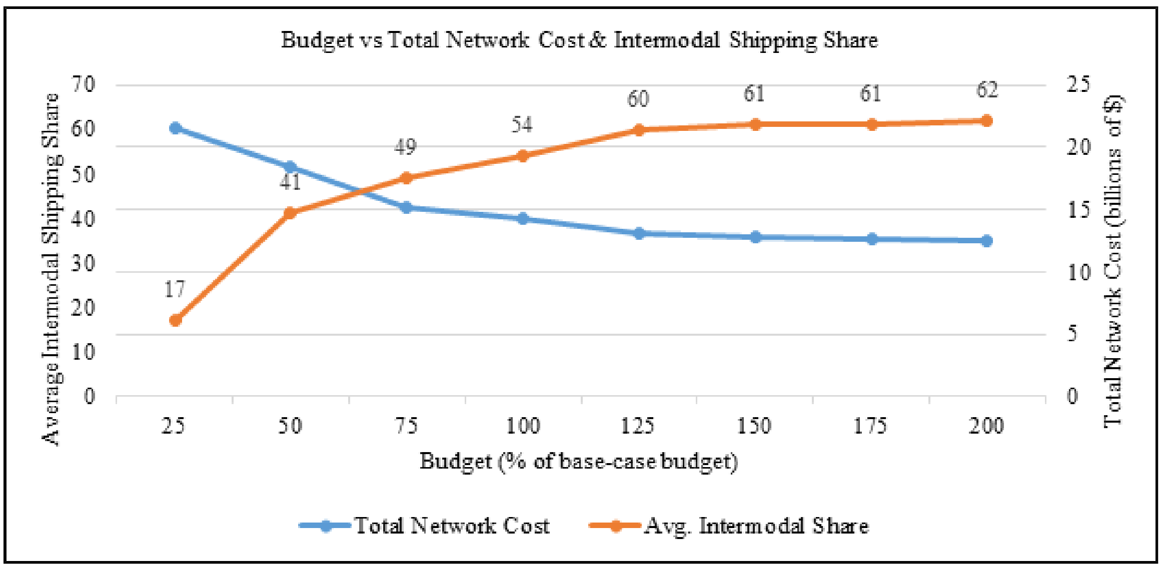


Figure 2.3: Effect of budget on total network cost and average intermodal shipping share across the planning horizon

2.4.2.2 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 important locations that have the most significant impact on cost as well as cost comparisons between scenarios and against the base-case scenario. Figure 4 illustrates these cost comparisons for optimal solutions with ten experiments.

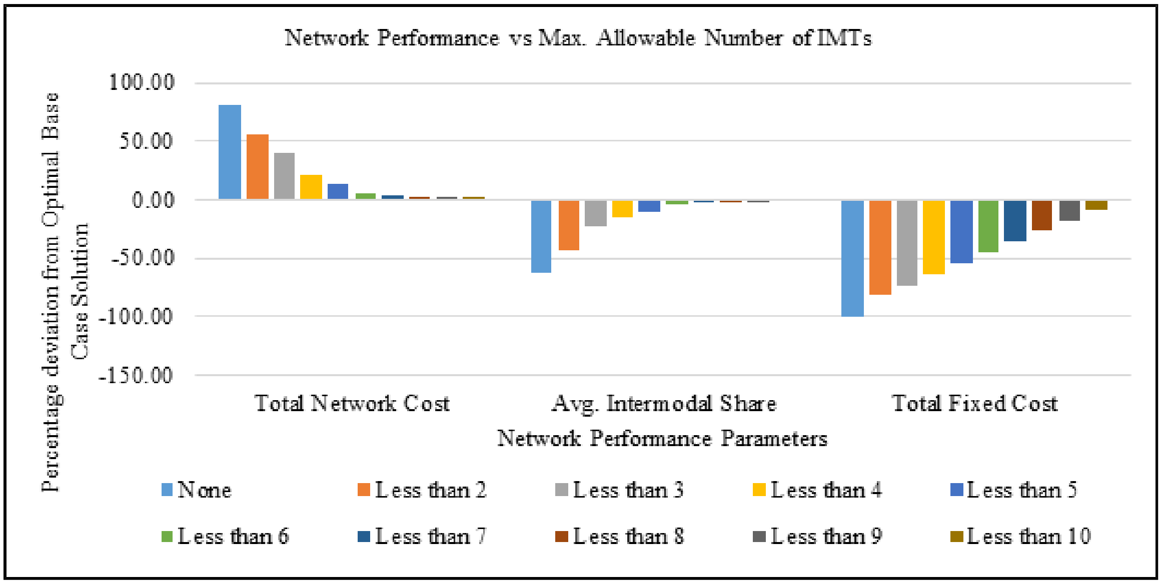


Figure 2.4: Deviation of Total Network Cost, Average Intermodal Share, and Total Fixed Cost in percentage from Optimal base-case for different limitations on the number of IMTs

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. 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 case of at most four IMTs, 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 adding 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 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).

2.4.2.3 Impact of Excessive Demand

The FAF[4] dataset gives us a network with balanced supply and demand, but often there are periods when demand exceeds the available supply for a given time-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 an increased total demand, so demands are satisfied from any shipper with available supply during these months. Figure 5 shows that inventory starts to build from May to September to meet the excessive demand from October to December.

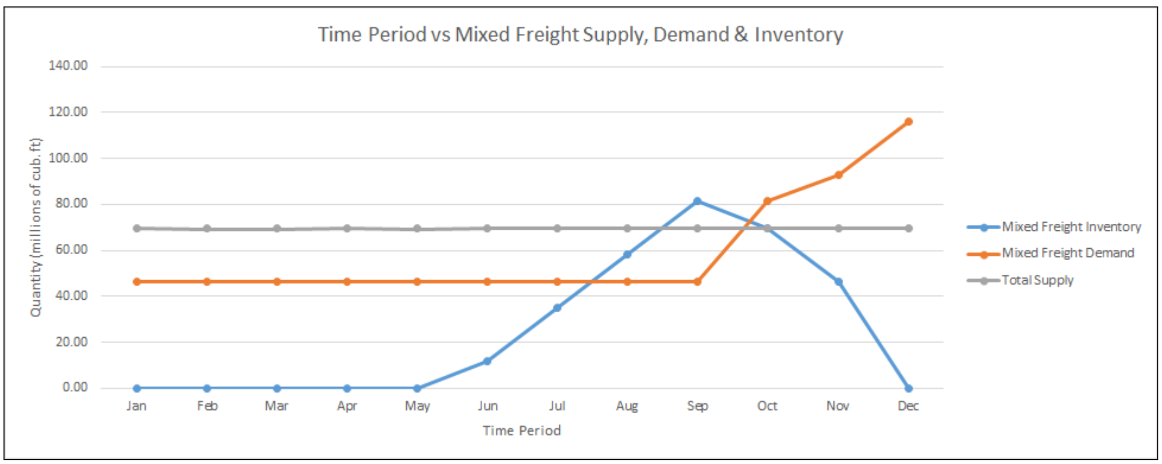


Figure 2.5: Supply, Total Demand and Inventory for Mixed Freight over the planning horizon

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 6 shows that 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 on how the model can help decision-makers influence the design of IMTs and/or nearby facilities for the locations where holding inventory can be 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.

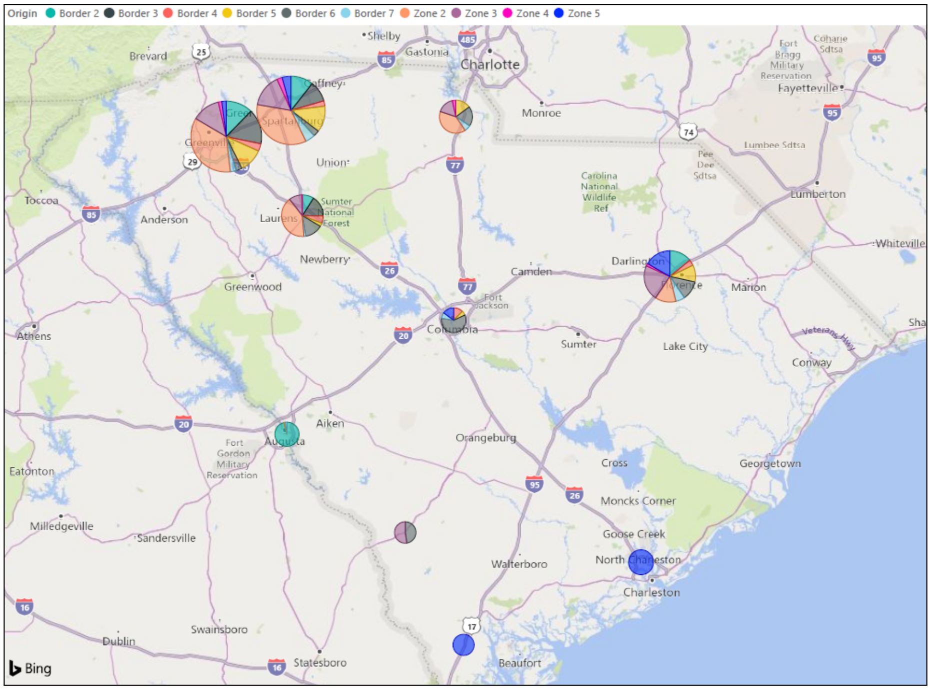


Figure 2.6: Mixed Freight inventory across the planning horizon by volume (cub.ft.) at IMT locations with respect to the Shipper/Origin

2.5 Conclusion and Future Work

A multi-period mixed-integer linear programming model 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 allow a consignee to demand freight from a specific shipper or any shipper. A flexible network 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, demands for time-periods.

The results show the importance of Columbia's location as an IMT. The regions with higher supply or demand of freight volume tend to have higher utilized IMTs and impact the total network cost most. 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 number of IMTs in intermodal network show how we can tradeoff intermodal shipping share and total network cost with budget investment in opening IMTs.

There are some clear directions for future research. One is that the current model structure 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 realist 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 IMTs that support rail-rail. rail-road, and rail-marine.

A second future research direction involves allowing key parameter to reflect the uncertainties seen in practice. The current model 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 parameter would add significant value to the model and results.

Finally, finding exact solutions to larger problems that likely be demanded by decision-makers will become computationally exhausting or even intractable. A decomposition approach along with heuristics can provide good quality solutions in a practically feasible computation time.

Chapter 3

A Stochastic Two-stage Model for Intermodal Terminal Location and Freight Distribution under Facility Disruptions

3.1 Introduction

Intermodal transportation is defined as the transportation of freight in a standardized container from shipper to customer using at least two modes of transportation, without repacking of freight, with the change of modes only allowed at the intermodal terminals. These modes typically associated with freight transportation are rail, truck, barge, and air. Intermodal transportation can improve the efficiency of a collaborative transportation network by taking advantage of favorable features of different modes of transportation that are available in a specific situations. For example, intermodal transportation can be more economical for long hauls because loads can be consolidated at intermodal terminals (IMTs) to take advantage of economies of scale. On the other hand, direct shipping by trucks can be more economical and quicker for shorter hauls because it does not require additional material handling at the IMTs. Therefore, delivering freight on a freight network utilizing both intermodal and direct shipping will lead to an overall reduction in freight shipping costs by optimally considering trade-offs in material handling, load consolidation, and delivery times. Such networks need dedicated IMTs to facilitate freight flow; they add an additional fixed cost that can be a one-time charge like the capital expenditure associated with construction or an annual payment like a lease. Therefore, an important decision in freight network design is, if IMTs are needed and, if they are, how many should be opened and where should they be located. For a comprehensive review on intermodal transportation, readers can refer to the work by Bontekoning et al. [20] and Agamez at al. [5].

Addressing uncertainty is one of the biggest challenges in planning. This is true in designing a freight transportation network because disruptions can cause chaos with missed customer deliveries and buildup of freight in locations that are unable to accommodate it. According to Snyder [68], facility locations decisions are prone to inaccuracy due to fluctuations in parameters of the problem and can be difficult and costly to reverse. The uncertainty can lead to partial or complete disruption of the intermodal freight network if resilience is not a goal of the design. Sources of uncertainties can be internal such as fluctuating available transportation capacities, change in transportation costs, or external like natural disasters (e.g., hurricanes, floods, earthquakes, etc.). Miller-Hooks [57] states that, "Even minor disruptions can have effects that ripple through the network, resulting in major reductions in system efficiency with nation-wide or even global impact." In 1989, Hurricane Hugo struck South Carolina as a Category 4 Hurricane and impaired 18,000 miles of highways in South Carolina alone [44]. In 2005, Hurricane Katrina and Hurricane Rita made landfall in Louisiana less than a month apart. The cost to repair transportation facilities was approximated to be more than $2.1 billion, and CSX's estimated reconstructions costs were between $250 million and $300 million [41]. By explicitly considering disruptions in the siting of IMTs, it will help to reduce the total freight network cost over the long-term and it will enable the network to be more resilient or at least perform as well as the networks designed using deterministic models.

In this study, we develop a methodology to determine the optimal IMT locations (if any) under disruptions which can occur at either supplier facilities or IMTs or both. These disruptions are uncertain and can range from no disruption to fully disrupted. Using historical data, a finite number of disruption scenarios, facilities (suppliers and IMTs) impacted, associated probabilities and disruption duration are computed. The discrete probability distribution associated with scenarios is used to model the intermodal freight network under uncertainty with the objective to minimize the long-term, expected total freight network cost. The model developed in Badyal et al. [15] is used as the basis and modifications are made to adapt it to the current research problem. A two-stage stochastic model is developed, the first stage decides locations of the IMTs, and in the second stage, freight distribution decisions are made. Since the intermodal facility location problem is a well known NP-hard problem, a decomposition approach is used. First,the L-shaped method is applied to decompose the problem and reduce the computational time required as compared to the extensive form. Then, level decomposition is applied to stabilize the iterations which further reduces the computational time.

To illustrate the value of the developed methodology, it is applied using South Carolina as a case study. Some states in the U.S. like South Carolina are more prone to hurricanes than the others, and the hurricanes can cause severe infrastructure damage due to high winds, heavy rainfall, inland flooding, storm surges, or tornado outbreaks [71]. Most of these hurricanes occur during a certain period of a year, called the hurricane season, as shown in Figure 3.1. Hurricanes can impact the shippers and intermodal terminals by disrupting production or operation at a facility, and thereby reduce the net supply available or throughput capacity at an IMT during the disruption period. The case study uses historical data for hurricanes to generate possible real world scenarios containing information regarding hurricane tracks, impacted facilities (shipper or an IMT), and disruption duration. The results are discussed and sensitivity analysis is performed to study the impact of disruptions, and direct shipping costs on long-term benefits of the stochastic model against the deterministic model.

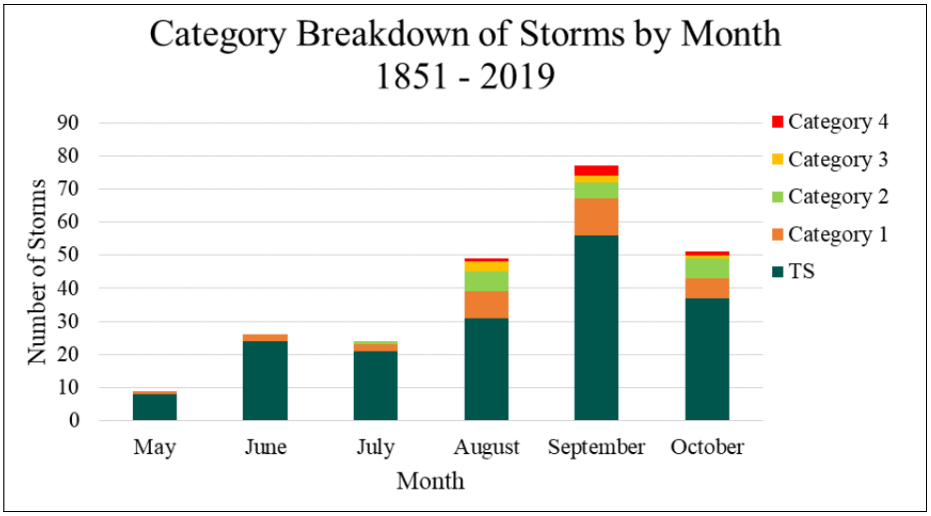


Figure 3.1: Number of hurricanes and tropical storms that impacted South Carolina between 1851 and 2019 (Source: South Carolina Department of Natural Resources)

3.2 Literature Review

There has been a growing interest in research towards facility/hub/IMT location problems under uncertainty, which is an inherent characteristic in many real world operations. There are many sources of uncertainty, which when not accounted for in the planning process, can result in gross error in estimate. Although uncertainty is a well known phenomenon, it has only been addressed recently due to its complexity. According to Shahabi et al. [67] literature for hub location problems under uncertainty is limited. This study aims to contribute to this body of work by modeling the inherent uncertainty in a disruption prone intermodal freight network. Readers interested in the evolution of research on intermodal transportation, classification of research, major publication trends or influential papers can refer to Mathisen et al. [54].

The following review for facility/hub/IMT location problems with uncertainty is divided into two parts based on the source of uncertainty: (1) generalized uncertainties in transportation network (no given source), and (2) uncertainties due to natural disasters.

3.2.1 Generalized Uncertainties in Input Parameters

A transportation network's operations have several sources of uncertainties such as the supply available at the shipper, the week-to-week demand of a customer, the fuel price which affects transport cost, and travel time. The nature of uncertainty in parameters (e.g., probability distribution) depends on the type of problem being studied.

Snyder et al. [69] presented a study for reliable facility location problem with disruptions, where customers are assigned to a nearest back-up facility if the originally assigned facility is disrupted. Lagrangian relaxation method was applied to solve the problem. Cui et al. [32] developed a reliable facility location model to mitigate the disruptions proactively. Their study presented two approaches for facility location and flow allocations: a Mixed Integer Linear Programming (MILP) based model solved using a custom-Lagrangian Relaxation algorithm to get exact solution, and a Continuum Approximation (CA) based model to get fast approximate solutions for large-scale problem. Peng et al. [62] presented a p-robust logistics network design problem (p-LNDP), which bounded the maximum shipping cost for all facility disruption scenarios under a specified upper bound/budget. Their model allows the decision makers to make trade-off between the initial facility cost investment and maximum disruption scenario budget. Contreras et al. [30] studied the uncapacitated hub location problem for demand uncertainty, and independent and dependent transportation cost uncertainties. A Two-stage model was developed to minimize facility location costs and expected transportation costs and solved using Sample Average Approximation (SAA) and benders decomposition. Demir et al. [33] proposed a model for green intermodal network design problem against demand and travel-time uncertainty. Their model supports multiple objectives by taking weighted sum of transportation costs, time-related and CO_2 emission related costs. The demand scenarios were generated using SAA and chance-constraints were used to achieve a service level against travel-time uncertainties.

Shahabi et al. [67] proposed a robust optimization based model to hedge against uncertainty in demand with unknown probability distribution. The original model developed was a mixed integer nonlinear formulation which is then transformed to a mixed integer conic quadratic formulation. They further linearized the conic model to a linear relaxed formulation which provides optimal solutions for all tested cases at reduced computational time. Merakli et al. [56] proposed a robust p-hub median problem under two types of demand uncertainty scenarios. The compact models presented are MILP based and solved using Bender's decomposition.

Fotuhi et al. [38] developed a robust optimization based model to tackle the intermodal network expansion problem under supply and demand uncertainty. The critical decisions are whether to open new terminals or expand the existing terminals, or retrofit the rail links. Their study is based on the works presented by Meng et al. [55] and Miller-Hooks et al. [57]. Fotuhi et al. developed a hybrid Genetic Algorithm (GA) to solve their model along with column-generation and shortest path label-setting algorithm. Yang et al. [82] addressed the issue of insufficient information or vagueness in uncertain parameters by using fuzzy random variables. Their model minimizes expected transportation costs and travel time and was solved using a Multi-start Simulated Annealing (MSA) algorithm.

Uddin et al. [74] presented a model for multi-commodity intermodal freight routing problem under disruptions. Their model considers link disruptions, node disruptions and IMT disruptions and was solved by using SAA algorithm. Uddin et al. [75] extended their prior work presented in [74] by dropping the assumption of knowledge of the probability distribution for uncertain parameters. The robust optimization based modeling approach uses symmetric random variables and relies on mean values and uncertainty intervals. Wang et al. [80] developed a model to design road-rail intermodal network under fuzzy uncertainty for demand, cost, and time. A bi-objective formulation was presented which is transformed to a MILP using weighted sum of objectives and was solved using Memetic Algorithm (MA) which utilizes genetic search method along with some local search strategies.

3.2.2 Uncertainties Due to Natural Disasters

A separate body of work has sought to develop a reliable transportation network against disruptions caused by natural disasters. The nature of uncertainty is defined by the type of natural disaster itself.

Barbarosoğlu et al. [16] developed a two-stage stochastic model for a multi-commodity, multi-modal transportation network. Their study dealt with urban transportation planning of first-aid commodities to earthquake affected areas under uncertainty in capacity, supply, and demand. After an earthquake signal, usable supply and operational arc capacities are realized which are used, in the first-stage, to allocate supply to other nodes before any demand is realized. In the second-stage, supply is fixed and demand and second-stage arc capacities are realized which are used to determine the final flow allocation. The authors solved for a exact solution under finite number of scenarios using a commercial solver. Chang et al. [27] developed a two-stage model for rescue equipment shipping under uncertain flooding levels and finite number of scenarios while minimizing the costs. In the first stage, rescue bases are located, then flooding level and location are realized which are used to determine the demands. In the second stage, flow allocations are performed. To represent the large number of possible realizations, SAA was used.

Rennemo et al. [64] developed a three-stage stochastic facility location and routing model for disaster response. Their model incorporates uncertainty in the state of infrastructure and demands. It is different from other studies as it allows for an additional recourse stage after demand and vehicle capacities are known but infrastructure information is still unknown. This information is only realized just before the second recourse action to modify routes is taken. Miller-Hooks et al. [57] presented a two-stage stochastic model for resilient intermodal freight network against disruptions caused by disaster events. In the first-stage, pre-disaster preparedness actions are taken, once disaster is realized the recourse stage makes post-disaster actions. The stochastic parameters were sampled from a probability distribution using Monte Carlo simulation and L-shaped method was applied to decompose the problem.

Marufuzzaman et al. [53] presented a model to design a reliable biofuel intermodal network against site-dependent probabilistic disruptions at intermodal terminals. Their study developed a methodology for generation of site failure probabilities using real world data and applied it to networks that are proned to flooding, hurricanes, and/or drought. The model was solved using accelerated bender's decomposition, where valid inequalities, Pareto-optimal cuts, knapsack inequalities are added to expedite the convergence and trust region method is applied to stabilize the iterations. Poudel et al. [63] designed a pre-disaster planning model for a multi-modal biofuel network against connecting links disruptions using the site disruption probability methodology developed by Marufuzzaman et al. [53]. The probability for link failure was generated by developing a spatial dependency between probability of a disaster and probability of disruption of a link. The model was solved using an enhanced Benders Decomposition algorithm to reduce the computational time.

The Intermodal Terminal Location Problem (IMTLP) under facility disruptions studied in this paper is fundamentally different from the previous literature. The intermodal network developed in this problem is capacitated, utilizes short-term inventory at IMTs, and freight distribution planning is multi-period. A decision is made on the number and location of IMTs before the uncertainty in supply and IMT throughput capacity is realized based on the possible disruption scenarios. Once the uncertainty/scenario is realized, a recourse is taken for freight distribution using the selected locations. The developed model can be applied to intermodal networks that are proned to disruptions which lead to shut down in operations at shippers and IMTs during any planning periods.

The case study presented later in this paper for intermodal facility location under hurricane disruptions also contributes towards a very scarce hurricane disruptions literature in IMTLP. Table 3.1 shows the literature that dealt specifically with natural disasters. The correlation indicated in the last column of the table refers to the correlation in occurrence of a natural disaster event/scenario among a group of facilities. Marufuzzaman et al. [53] developed a methodology for flood, drought and hurricane disruptions but it used site-dependent failure probabilities and assumed event probabilities are site independent. Poudel et al. [63] used site dependent disruption probabilities developed by Marufuzzaman et al. [53] to generate spatial correlation of failures between the disrupted nodes and the links in proximity, but their method does not provide information on group of facilities or links to be impacted by a single disruption event. This study uses historical data to generate hurricane scenario probabilities and the group of locations impacted under a particular hurricane occurrence. Therefore, hurricane occurrences at different locations are not independent.

Table 3.1: Literature Comparison of Reliable Models for Natural Disaster

Paper	Problem[1]	Solution Method	Disruption Source[2]	Disruption Type	Correlation
Barbarosoğlu et al. [16]	T	Exact-Solver	E	Supply, Capacity, Demand	x
Chang et al. [27]	L+T	SAA	F	Demand	✓
Rennemo et al. [64]	L+T	Exact-Solver	E	Demand, Capacity	x
Miller-Hooks et al. [57]	PDP	Integer L-shaped Method	B, TA, F, E, A	Capacity, Travel Time	x
Marufuzzaman et al. [53]	L+T	Accelerated L-shaped Method	F, H, D	Intermodal terminal	x
Poudel et al. [63]	L+T	L-shaped Method	F, H, D	Shipping Routes	x
This Paper	L+T	Level Decomposition	H	Supply, Intermodal terminal	✓

[1] L: Location, T: Transportation, PDP: Post-Disaster Planning

[2] A: IMT attack, B: Bombing, D: Draughts, E: Earthquake, F: Flood, H:Hurricane, TA: Terrorist attack

The authors are unaware of any previous work that 1) addressed an intermodal terminal location problem and freight distribution planning under shipper and intermodal terminal disruptions, and 2) developed a holistic methodology for hurricane disruptions. Improvement in computational efficiency using level decomposition has been shown for the generalized L-shaped method for two-stage stochastic models; however, to the best of the authors' knowledge, no study has applied and shown the computational benefit of level decomposition against the L-shaped method for IMTLPs. IMTLPs have an added complexity of additional variables due to many more choices that are available at each decision period (e.g., mode choice at IMT, intermodal shipping or direct shipping, multi-product demand, inventory decisions, satisfy or lose demand). In summary, the contributions of this paper are:

1. A two-stage stochastic model for intermodal terminal location and freight distribution planning under shipper and intermodal terminal disruptions.
2. A level decomposition solution approach that is later shown to improve computational efficiency as compared to the L-shaped method and the extensive form.
3. A holistic methodology for intermodal terminal location and freight distribution planning under hurricane disruptions.
4. Use of real world hurricane and storm data and machine learning techniques to identify expected hurricane tracks and determine the probabilities related to these tracks.
5. Strategies to mitigate impact of hurricanes and storms at the state level.

3.3 Problem Description and Methodology

The freight network contains two types of nodes: (1) shipper/customer (i.e., origins and destinations) and (2) IMT. Note that the shipper/customer nodes may have *both* shipper and customer roles. Three types of freight flows are allowed between shipper and customer in this model: (1) direct shipping, (2) intermodal shipping via two or more IMTs, and (3) intermodal shipping via only one IMT (consolidation). Unmet demand is allowed, which is penalized by a fixed cost per unit of unmet demand in the objective function. Pre-haul shipping or freight flows from customers to IMTs, end-haul shipping or freight flows from IMTs to customers, and direct shipping between shippers and customers are included and assumed to be uncapacitated. It is also assumed that these shipping routes are satisfied by trucks that are readily available under normal circumstances. The network of IMT nodes with shipper/customer nodes are assumed to be fully connected by the road-network. The IMT nodes are also fully connected for a wider variety of mode types, including rail. Figure 3.2 illustrates the type of intermodal freight network that is considered in this study.

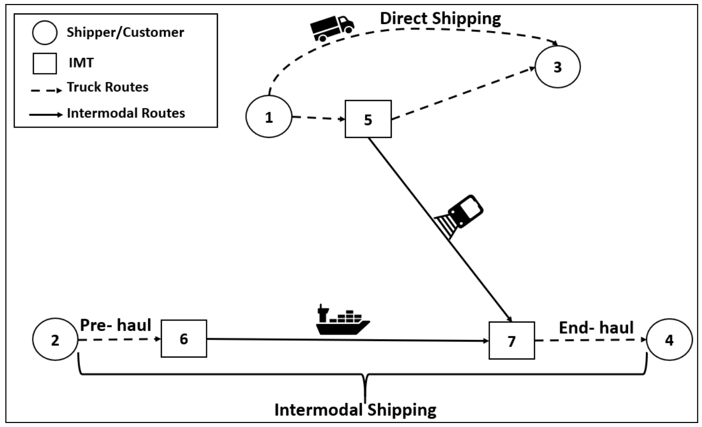


Figure 3.2: A generic intermodal freight network

Several assumptions are utilized to reflect the practical situation:

1. A fixed cost is charged to open an IMT and IMTs can be opened during any time-period within the planning horizon.

2. IMTs can be closed in any time period after they are opened. Hereinafter, IMT status is referred to as whether an IMT is open or closed in a time-period.

3. The total fixed cost to open IMTs cannot exceed a specified budget.

4. Intermodal shipping has limited capacity and the frequency with which modes operate (e.g., number of times trains run between IMTs) can be restricted.

5. The freight arriving at/departing from an IMT incurs a unloading/loading cost.

6. There is an inventory holding cost for freight stored at an IMT for more than one period.

7. IMTs have limited storage space, which is reflected as an upper bound on inventory, that can be held in any period.

8. There is an upper limit on throughput at the IMTs to reflect limited material handling equipment. The limit includes freight inflows from other IMTs or shippers and freight outflows to other IMTs or customers.

3.3.1 Hurricane Disruptions

Hurricanes can cause damages via flooding, storm surge, tornadoes, and high wind. This study focuses exclusively on wind damage. The reason for this assumption is that wind damage is predictable using the tracks and category of storms, whereas damages due to other factors cannot be readily quantified due to their dependency on geographical factors.

Wind damage from hurricanes can have devastating effects on infrastructure. They include power outages, water supply outages, and structural damages that can take several days to several months to be restored/repaired [58]. This study groups hurricanes into one of six categories based on the Saffir-Simpson hurricane wind scale: (1) TS (39-73 mph), (2) H1 (74-95 mph), (3) H2 (96-110 mph), (4) H3 (111-129 mph), (5) H4 (130-156 mph), and (6) H5 (¿157 mph) [58]. Any storm with a wind speed less than 39 mph is assumed to cause no damage and disruption. The area of impact for storms with higher wind speeds is assumed to be 100 miles from the eye of the hurricane [76]. The degradation of hurricanes after landfall is not modelled and is beyond the scope of this research. The hurricane category and the track are assumed to be both independent and stochastic. The impacts of hurricanes are explicitly considered in the model by using discrete and finite realistic scenarios generated from available real-world data. Each scenario carries information regarding both the category and track of a hurricane. The category determines how long a shipper node or IMT node is shut down, and the track determines which shippers and/or IMT nodes are impacted.

The national hurricane database HURDAT2 [45] and k-means clustering were used to generate category and track probability distributions. Using HURDAT2, information about a hurricane's category, its germination point, midway point and termination point within the region of study are collected and refined for the geographical area of interest. The refined database was then used to generate probability distributions for each hurricane category based on their numbers since the creation of the HURDAT2.

The k-means clustering technique was used to define the probability distribution of tracks based on similar tracks of hurricanes over the past years. This technique was chosen because it creates clusters depending on the variance within the elements of a cluster and results in clusters that are homogeneous [31]. Moreover, it lets the user select the number of clusters (k) which allows an analyst to intervene if a particular value of k produces meaningless results. The silhouette-coefficient is calculated for different values of 'k', which helps to determine the optimal number of clusters 'k*' to be formed. The probability of occurrence of a hurricane track depends on the number of hurricanes belonging to the parent cluster that best represents it.

The methodology for generation of hurricane categories and tracks for the state of South Carolina is presented later in Results section.

3.4 Mathematical Models

This section contains details of two mathematical models used to address the research questions. The first is a L-shaped method based on a two-stage model which is subsequently used as the basis for a Level decomposition based two-stage model. Level decomposition helps in stabilizing the iterations as compared to the L-shaped method by keeping the next iteration solution close to a stabilization center which is projected onto a level set. The definition of stabilization center depends on the user and will be discussed later.

3.4.1 Notation

Sets

N	shipper and/or customer nodes
H	candidate intermodal terminal nodes
P	products
M	transportation modes
T	time periods
Ω	scenarios $\{\omega_1, ..., \omega_n\}$

Parameters

B	budget for opening IMTs for the entire planning horizon ($)
$C_i^t(\omega)$	throughput capacity of IMT i in period t and scenario ω (units)

CD^t_{kgp}	direct shipping cost to move product p between shipper k and customer g in period t ($ per unit)
CE^t_{igp}	transportation cost to move product p from IMT i to receiver g using trucks in period t ($ per unit)
CF	penalty cost for unmet demand ($ per unit)
CH^t_{ip}	holding cost for product p at IMT i in period t (per unit)
CI^t_{ijmp}	transportation cost to move product p from IMT i to IMT j using mode m in period t ($ per unit)
CL^t_{ip}	loading cost for product p at IMT i in period t ($ per unit)
CP^t_{kip}	transportation cost to move product p from shipper k to IMT i using trucks in period t ($ per unit)
CU^t_{ip}	unloading cost for product p at IMT i in period t ($ per unit)
D^t_{gkp}	demand for product p belonging to shipper k at customer g in period t (units)
F_i	fixed cost for opening an IMT i $\in$ H ($)
HC^t_i	inventory holding capacity of IMT i in period t (units)
$\mathrm{p}(\omega)$	probability of realizing scenario ω
$\mathrm{S}^t_{kp}(\omega)$	supply of product p available at shipper k in period t under scenario ω (units)
TI^t_{ijm}	maximum number of trips available between IMTs i and j using mode m in period t (trips)
VM_m	volume capacity of mode m (ft^3)
VP_p	volume of one unit of product p (ft^3)
VT	volume capacity of a truck (ft^3)

Decision Variables

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

$f^t_{gkp}(\omega)$	number of units of unmet demand for product p belonging to shipper k required by customer g in period t under scenario ω
$h^t_{ikp}(\omega)$	number of units of product p belonging to shipper k held as inventory at IMT i in period t under scenario ω

$l_{ikp}^{t}(\omega)$ number of units of product p belonging to shipper k loaded at IMT i in period t under scenario ω

$q_{kip}^{t}(\omega)$ number of units of product p shipped from shipper k to IMT i using trucks in period t under scenario ω

$r_{jgkp}^{t}(\omega)$ number of units of product p belonging to shipper k moved from IMT j to customer g using trucks in period t under scenario ω

$u_{ikp}^{t}(\omega)$ number of units of product p belonging to shipper k N unloaded at IMT i in period t under scenario ω

$w_{kgp}^{t}(\omega)$ number of units of product p direct shipped from shipper k to customer g in period t under scenario ω

$x_{ijmkp}^{t}(\omega)$ number of units of product p belonging to shipper k moved from IMT i to IMT j using mode m in period t under scenario ω

3.4.2 Two-stage Stochastic Model

A two-stage stochastic model is developed in which the master problem/first-stage [**MP**] defines the optimal number of IMTs and their locations within a fixed budget. Using these fixed locations, the recourse function/second-stage [**SP**] optimizes the freight flows for each of several disruption scenario. The two-stage model minimizes the total fixed cost and expected variable freight flow costs. The first-stage IMT selection decisions are made at the start of planning horizon and, then, uncertainty is introduced through scenarios. That is, supply and IMT throughput information are revealed; then the recourse action (i.e.,freight-flow) decisions are made for specific scenarios using [**SP**].

Two-stage models are known to perform well for facility location models because they separate hard to solve facility location problems that require integer variables from the easier to solve freight flow problem that used continuous variables. This approach can be leveraged in decomposition techniques that reduce the computational time which is typically a concern for these types of problems.

Master Problem/First-Stage [MP]

$$\text{Minimize} \sum_{i \in H} F_i \xi_i + \sum_{\omega \in \Omega} p(\omega) Q_\omega(\xi) \tag{3.1}$$

Subject to,

$$\sum_{i \in H} F_i \xi_i \leq B \tag{3.2}$$

$$\xi_i \in \{0,1\} \qquad \forall i \in H \tag{3.3}$$

where ξ is a vector representing the of status (open/close) of all the IMTs, $Q_\omega(\xi)$ is the fixed recourse function, which is calculated by solving the **[SP]** shown below. Note that $Q_\omega(\xi)$ is dependent on both which IMTs are open ('ξ') and the scenario ω.

The objective function (3.1) minimizes the sum of the total fixed costs plus the expected recourse costs. Constraint (3.2) ensures that budget for opening IMTs is not exceeded. Constraints (3.3) are the binary variable declarations. Since, the demand can be fulfilled by uncapacitated direct shipping, intermodal shipping, or unmet demand, the problem has a *relatively complete recourse*, which means given any **[MP]** solution, **[SP]** is always feasible.

Sub-Problem/Second-Stage/Fixed Recourse [SP]

$$\begin{aligned} Q_\omega(\xi) = \text{Minimize} & \sum_{i,j,m,k,p,t} CI^t_{ijmp} x^t_{ijmkp}(\omega) + \sum_{k,i,p,t} CP^t_{kip} q^t_{kip}(\omega) + \sum_{j,g,k,p,t} CE^t_{jgp} r^t_{jgkp}(\omega) \\ + \sum_{i,k,p,t} CU^t_{ip} u^t_{ikp}(\omega) + & \sum_{i,k,p,t} CL^t_{ip} l^t_{ikp}(\omega) + \sum_{i,k,p,t} CH^t_{ip} h^t_{ikp}(\omega) + \sum_{k,g,p,t} CD^t_{kgp} w^t_{kgp}(\omega) \\ + \sum_{g,k,p,t} CF f^t_{gkp}(\omega) & \end{aligned} \tag{3.4}$$

Subject to,

$$\sum_{\substack{j\in H\\ j\neq i}}\sum_{m\in M} x^t_{jimkp}(\omega)+q^t_{kip}(\omega)+l^t_{ikp}(\omega)=\sum_{m\in M}\sum_{j\in H} x^t_{ijmkp}(\omega)+\sum_{\substack{j\in H\\ j\neq i}}\sum_{\substack{g\in N\\ g\neq k}} r^t_{jgkp}(\omega)+u^t_{ikp}(\omega),$$
$$\forall i\in H,k\in N,p\in P,t\in T, \tag{3.5}$$

$$h^t_{ikp}(\omega)=h^{t-1}_{ikp}(\omega)+u^t_{ikp}(\omega)-l^t_{ikp}(\omega), \qquad \forall i\in H,k\in N,p\in P,t\in T \tag{3.6}$$

$$w^t_{kgp}(\omega)+\sum_{j\in H} r^t_{jgkp}(\omega)+f^t_{gkp}(\omega)\geq D^t_{gkp}, \qquad \forall g,k\in N: g\neq k, p\in P,t\in T \tag{3.7}$$

$$\sum_{i\in H} q^t_{kip}(\omega)+\sum_{\substack{g\in N\\ g\neq k}} w^t_{kgp}(\omega)\leq S^t_{kp}(\omega), \qquad \forall k\in N,p\in P,t\in T \tag{3.8}$$

$$\sum_{k\in N}\sum_{p\in P} x^t_{ijmkp}(\omega)VP_p\leq TI^t_{ijm}V_m, \qquad \forall i,j\in H: i\neq j, m\in M,t\in T \tag{3.9}$$

$$\sum_{\substack{j,m,k,p,\\ j\neq i}} x^t_{ijmkp}(\omega)+\sum_{\substack{j,m,k,p,\\ j\neq i}} x^t_{jimkp}(\omega)+\sum_{k,p} q^t_{kip}(\omega)+\sum_{\substack{g,k,p,\\ k\neq g}} r^t_{igkp}(\omega)\leq C^t_i(\omega)\xi, \qquad \forall i\in H,t\in T \tag{3.10}$$

$$\sum_{k\in N}\sum_{p\in P} h^t_{ikp}(\omega)\leq HC^t_i, \qquad \forall i\in H,t\in T \tag{3.11}$$

$$q^t_{kip}(\omega),x^t_{ijmkp}(\omega),r^t_{jgkp}(\omega),w^t_{kgp}(\omega),u^t_{ikp}(\omega),l^t_{ikp}(\omega),h^t_{ikp}(\omega)\geq 0$$
$$\forall k,g\in N: k\neq g, i,j\in H: i\neq j, m\in M,p\in P,t\in T,\omega\in\Omega \tag{3.12}$$

The objective function (3.4) minimizes the freight flow variable costs for a scenario given and open IMTs specified by the optimal 'ξ' from **[MP]**.The variable costs includes intermodal shipping cost, direct shipping cost, unmet demand's penalty cost, prehaul and endhaul costs, loading and unloading costs, and inventory holding cost. Constraints (3.5) and (3.6) ensure flow-balance at an IMT. Constraints (3.7) ensure that customer demand is satisfied through direct shipping, intermodal shipping, and/or unmet demand. Constraints (3.8) are supply capacity constraints that limit the amount each shipper can supply to no more than their production capacity in each time-period. Constraints (3.9) are intermodal link capacity constraints that restrict the total freight volume carried between the two IMTs on a mode type to no more than the volume capacity of that mode type for a each time-period. Constraints (3.10) are IMT throughput capacity constraints that ensure total inflow and outflow of freight at an IMT does not exceed its capacity. Constraints (3.11) are IMT inventory capacity constraints while constraints (3.12) are variable declarations.

Dual Sub-problem [DSP]

Since the second stage is a linear programming problem, the dual information can be used in an exact solution decomposition technique like the L-shaped method. Constructing the dual is well known [**?**] and the dual for this problem is presented below using vector notation.

$$Q_\omega(\xi) = \text{Maximize} \quad \pi_\omega J_\omega(\xi) \tag{3.13}$$

$$\text{Subject to,} \qquad \pi_\omega \in \Pi_\omega \tag{3.14}$$

where Π_ω is the feasible region of the dual sub-problem. For a given scenario ω, π_ω is a vector of dual variables of the [**DSP**] and $\pi_\omega J_\omega(\xi)$ is the objective function of dual sub-problem. By strong duality, this is equal to the [**SP**] objective value $Q_\omega(\xi)$ at the optimal solution. As the problem has relatively complete recourse, the [**SP**] and [**DSP**] will always have optimal solution values that are equal.

3.4.3 The L-shaped Method

The L-shaped method developed by Slyke et al. [79] is an exact solution decomposition method and helps reduce the computational effort required to find the optimal solution of a separable mixed integer linear programming problem. Since this problem has a relatively complete recourse no *feasibility cuts* are needed and all discussions in the sections thereafter will be limited to optimality cuts only. A multi-cut approach developed by Birge et al. [19] is used here instead of the single-cut version. In multi-cut version for each scenario, a optimality condition is checked, and if violated, a valid inequality (optimality cut) is added to the master problem using that scenario's dual information. Whereas in single-cut version, a single optimality condition is checked, and if violated, a single cut is added to master problem using dual information from all the scenarios. Multi-cuts are stronger or have more information, i.e. they eliminate more sub-optimal solutions as compared to single-cuts. Single-cut version adds only one optimality cut per iteration, whereas multi-cut version at worst can add optimality cuts equal to the number of scenarios. There is a trade-off between the two approaches: (1) multi-cut version increases the size of the master problem (thus more computation effort to solve) but lead to stronger cuts, and (2) single-cut version leads to a smaller master problem relative to multi-cut version but weaker cuts. Since our starting master problem has only one constraints we choose multi-cut version.

L-shaped method is an iterative algorithm which starts with a relaxed master problem by dropping a set of constraints and thus optimizes an approximation of the original problem. For a minimization problem, each iteration produces a lower bound from the relaxed master problem and an upper bound from the sub-problem and first-stage solutions. The objective function value to the relaxed problem that is an approximation of the original problem is improved at each iteration by adding valid inequalities for each scenario. These are known as optimality cuts. The iterations are performed until a stopping criteria is met. The overall idea of the algorithm is to reach an optimal solution before adding all the information back to the relaxed problem so the computational efficiency is improved. For more information on decomposition methods readers can refer to Pay [65].

The Benders master problem [**LS-MP**] is a reformulation of the [**MP**]. The variable θ_ω is used as a dummy variable for each scenario $\omega \in \Omega$ that requires adding a set of constraints (3.17) to [**LS-MP**].

LS-MP

$$\text{Minimize} \sum_{i \in H} F_i \xi_i + \sum_{\omega \in \Omega} p(\omega) \theta_\omega \tag{3.15}$$

Subject to,

$$\sum_{i \in H} F_i \xi_i \leq B \tag{3.16}$$

$$\theta_\omega \geq Q_\omega(\xi) \qquad \forall \omega \in \Omega \tag{3.17}$$

$$\xi_i \in \{0, 1\} \qquad \forall i \in H \tag{3.18}$$

[**LS-MP**] is now relaxed to a Benders restricted master problem [**LS-RMP**] which contains a subset (3.21) of the set of constraints (3.17).

LS-RMP

$$\text{Minimize} \sum_{i \in H} F_i \xi_i + \sum_{\omega \in \Omega} p(\omega) \theta_\omega \tag{3.19}$$

Subject to,

$$\sum_{i \in H} F_i \xi_i \leq B \tag{3.20}$$

$$\theta_\omega \geq \pi_\omega J_\omega(\xi) \qquad \forall \omega \in \Omega, \pi_\omega \in V_\omega^{iter} \subseteq XP(\Pi_\omega) \tag{3.21}$$

$$\xi_i \in \{0, 1\} \qquad \forall i \in H \tag{3.22}$$

where V_ω^{iter} is a subset of extreme points of feasible region of [**DSP**] for a given scenario $\omega \in \Omega$. π_ω is an extreme point of the feasible region of [**DSP**] Π_ω. Constraints (3.21) are also known as optimality cuts and are added only for violated scenarios (i.e. $\theta_\omega < Q_\omega(\xi)$ or constraint 3.17) thus leading to a restricted master problem (RMP).

3.4.4 The Level Method

One of the drawback of L-shaped method is instability in iterations, even when close to an optimal solution. This instability is typically seen as oscillations when approaching optimal solution and taking large steps away from current solution in the initial iterations [**?**]. The level decomposition algorithm based on the level method developed by Lemarechal et al. [50] is applied to "regularize" the L-shaped method, using a user-defined stability center and a level parameter 'F_{lev}' [65]. The stability center used for this study and in general is the solution of the previous iterate as it prevents the algorithm from taking very large steps away from the current solution.
The master problem [**MP**] is reformulated to a restricted quadratic programming problem [**LD-RMP**] and thus the new model is a Mixed Integer Quadratic Programming (MIQP) model. The master problem of the new model is presented below and the fixed recourse function remains the same as [**SP**],

LD-RMP

$$\text{Minimize} \sum_{i \in H} (\xi_i - \xi_i^*)^2 \tag{3.23}$$

Subject to,

$$\sum_{i \in H} F_i \xi_i \leq B \tag{3.24}$$

$$\theta_\omega \geq \pi_\omega J_\omega(\xi) \qquad \forall \omega \in \Omega, \pi_\omega \in V_\omega^{iter} \subseteq XP(\Pi_\omega) \tag{3.25}$$

$$\sum_{i \in H} F_i \xi_i + \sum_{\omega \in \Omega} p(\omega)\theta_\omega \leq F_{lev}^{iter} \tag{3.26}$$

$$\xi_i, \xi_i^* \in \{0, 1\} \qquad \forall i \in H \tag{3.27}$$

where $F_{lev}^{iter} = F_{low}^{iter} + \lambda(F_{up}^{iter} - F_{low}^{iter})$ for a given parameter $\lambda \in [0, 1]$. F_{low}^{iter} is the lower bound of the **[LD-RMP]** upto the iteration '*iter*' and is set equal to F_{lev}^{iter-1} when the level set is empty. F_{up} is the upper bound at iteration '*iter*', and 'ξ^*' is the stability center which is equal to the IMT status from the previous iteration.

The objective function (3.23) and constraint (3.26) project the stability center onto the level set defined by **[LD-RMP]** to find the next iterate near the current solution and thus stabilize the iterations. The value of 'λ' used for this study is 0.2929. The readers interested in more details of two-stage decomposition methods can refer to Lemarechal et al. [50], Wolf et al. [81], and Pay [65].

3.5 Results and Discussion

The following experiments were performed on Clemson University's Palmetto Cluster. The hardware specifications for the node used are: Intel Xeon processor, 24 cores, and 400GB RAM. Julia programming language was used for mathematical optimization, Gurobi v9.1.0 commercial solver was used for all the solution algorithms applied, and Python programming language was used for data analysis and machine learning applications.

3.5.1 Computational Experiments:

The extensive form or the single large mixed integer problem, the two-stage model using L-shaped method, and the two-stage model using level decomposition are now compared. The number of scenarios are increased to study the impact on computation time within and across all the methods. A time limit of 24 hours or 86400s is used for extensive form, and the stopping criteria for both decomposition methods is a relative gap less than or equal to 10e-5 between the upper and lower bounds or until all the optimality cuts are added.

The algorithms used for the L-shaped method and Level decomposition are presented in Appendix A.

Table 3.1: Computation time by Solution Algorithm

Number of Scenarios	Computation time (in seconds)		
	Extensive Form	L-shaped	Level Decomposition
1	382	731	622
4	>86400*	978	841
6	9631	1254	995
8	>86400*	1345	1114
10	26665	1618	1388
15	>86400*	2033	1763

* Reached 24hrs time limit.

Table 3.1 shows that for the extensive form although there is no particular pattern with increase in number of scenarios, the solution time seems to increase considerably as compared to other two decomposition methods. Only for the case of '1 scenario' the extensive form outperforms both L-shaped and level decomposition algorithm, but as number of scenarios increase further L-shaped and level decomposition outperform it. This is expected as the extensive form's number of variables and number of constraints increase non-linearly for this problem as the number of scenarios increase.

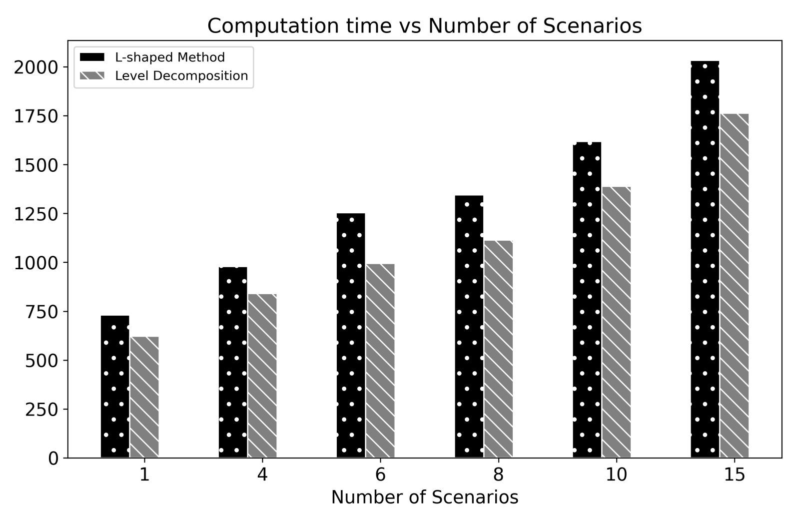


Figure 3.3: L-shaped and Level Method are tested against increasing number of scenarios to compare computation time.

Figure 3.3 shows the individual computation times and comparison between L-shaped and level decomposition methods. It is observed that level decomposition outperforms L-shaped method for all the cases, with an average computation time reduction of 15.7%. For both the decomposition methods the computation time increases as the number of scenarios increase, and the average increase in computation time between scenario cases is 23%.

It is evident from these experiments level decomposition provides a better computation time, and thus the rest of the experiments are performed using the level decomposition method.

3.5.2 South Carolina Case Study

The following experiments were performed on an rail-road intermodal network developed for the South Carolina case study presented in our previous work and for more details about how the input parameters are selected or developed readers should refer to Badyal et al. [15]. The supply and demand data was generated using the FAF4 (Freight Analysis Framework) dataset for the year 2018. The planning horizon for this study was divided into four time-periods or quarters: (1) Feb-Apr, (2) May-Jul, (3) Aug-Oct, and (4) Nov-Dec. Since, the regions available in FAF dataset are too large for the scope of this study the region is broken down in to five zones. Consolidation centers at five zones, seven border points, and Port of Charleston (PoC) are selected as shipper/customer nodes, and 13 IMT potential nodes are selected at major interstates and railroad intersections. The 13 shipper/customer nodes and 13 potential IMT nodes are shown in Figure 3.4 and Figure 3.5 respectively.

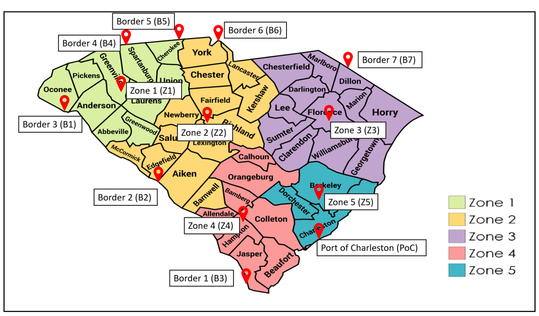


Figure 3.4: All 13 shipper/customer nodes and five zonal divisions. (Source: Badyal et al. [15])

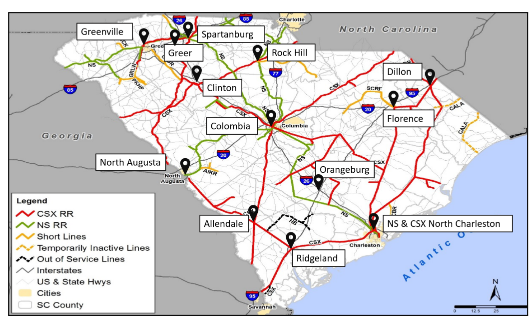


Figure 3.5: Major railroads, interstates, and potential intermodal locations. (Source: SC DOT, Badyal et al. [1], [15])

A total of seven products are selected based on highest shipping tonnage, two type of modes are assumed to be available between all the IMTs: Rail and Twin 53 ft container trailer trucks. Supply at customers from FAF4 data is increased by 10%, this provides an opportunity to test the use of inventory across the time-periods. Other data used for the parameters used in the case study are presented in Table 3.2 and 3.3. It is assumed, 1 Twenty-foot Equivalent Unit (TEU) = 1172 ft^3 and a container refers to a 53 ft container.

Table 3.2: Product types and related model input parameters

Parameters	Range/Values by Product*						
	B.C.	Coal	Coal-n.e.c	Gravel	M.F.	N.S.	Scrap
Loading/Unload Costs ($\$/ton$)	0.6-1.3	0.9-2	0.3-0.8	0.5-1.1	2.5-5.2	0.4-0.9	3.3-7.1
Holding Costs ($\$/ton$)	3-7	7-9	3-7	3-7	7-9	7-9	7-9

* Standard Classification of Transportation Goods: B.C. = Basic Chemicals, Coal-n.e.c. = Coal not elsewhere classified, M.F. = Mixed Freight, N.S. = Natural Sands

The Hurricane database or HURDAT2 was used to collect the data for hurricanes between years 1858-2018. Using the data points the tracks were developed for all the hurricanes on the Atlantic coast. Since the study is limited to the state of South Carolina, only the data points nearby the state were retained. The hurricanes are classified according to the wind speed to generate the probability of a particular category of hurricane. There were no ‘H5’ hurricanes that impacted the state and therefore this category was dropped from the analysis. The six categories selected include the categories TS, H1, H2, H3, H4, and an additional category of ’No Hurricane (NH)’. The NH category includes all the hurricanes that have wind speed less than 39mph. It is also assumed at most only one hurricane can occur in the quarter of Aug-Oct. This range of hurricane season seems to be a reasonable assumption as most of the hurricanes as previously discussed for the state occur during this period.

Table 3.3: Model input parameter values

Parameters	Range/Values
IMT Inventory Capacity (containers)	2200-2500
IMT Throughput Capacity (containers)	(22-25)*10^5
Intermodal trips (per quarter)	
(i) Rail	4,500-18,000
(ii) Twin 53 ft. Container Trailer Truck	(2.25-2.7)*10^5
Fixed Cost to Open IMT ($)	30M-40M
Budget ($)	520M
Mode Capacity (containers per trip)	
(i) Rail	200
(ii) Twin 53 ft. Container Trailer Truck	2

The probability of a particular category is calculated using the equation below,

$$\mathbb{P}[\text{Cat X}] = \left(\frac{\text{No. of storms of `Cat X'}}{\text{Total no. of storms}}\right)$$

It is assumed that a particular category storm disrupts operation of a shipper and an IMT for a fixed number of days. The total operational days in a year quarter are assumed to be '90'. As the wind speed increases it can be seen that number of disruption days increase. The input parameters related to hurricane and probabilities developed are shown in Table 3.4.

Table 3.4: Hurricane categories and related parameters

Parameters	Values by Strength Category					
	NH	TS	H1	H2	H3	H4
Disruption Duration (days)*	0	7	14	21	30	45
Number of Storms	32	60	39	23	9	6
Probability	0.189	0.355	0.231	0.136	0.053	0.036

* Source: National Hurricane center and Central Pacific Hurricane Center

k-means clustering is used to group similar hurricane tracks over the past into a single group and a total of 'k^*' clusters are formed. The data used for clustering included the germination location, midway-location and termination location of the hurricane. The optimal value, 'k^*' needs to be identified, for which the silhouette coefficient is used. The silhouette coefficient gives the goodness of a cluster and its value ranges from [-1,1]. A value closer to +1 means clustering is very distinct, a score of 0 would mean the difference in significant, and a score closer to -1 means wrong cluster assignments are made.

Clustering is performed for number of clusters between 2 and 40, and silhouette coefficient is calculated as shown in Figure 3.7. Maximum silhouette coefficient value is obtained at 2 clusters, followed by 3 and 5 clusters. But for k=2 and k=3 the clusters spread is too large relative to the geography of the state and thus were deemed not fit for this analysis. The next best value of k^*=5 is thus picked for further analysis. The final clusters are shown in Figure 3.7.

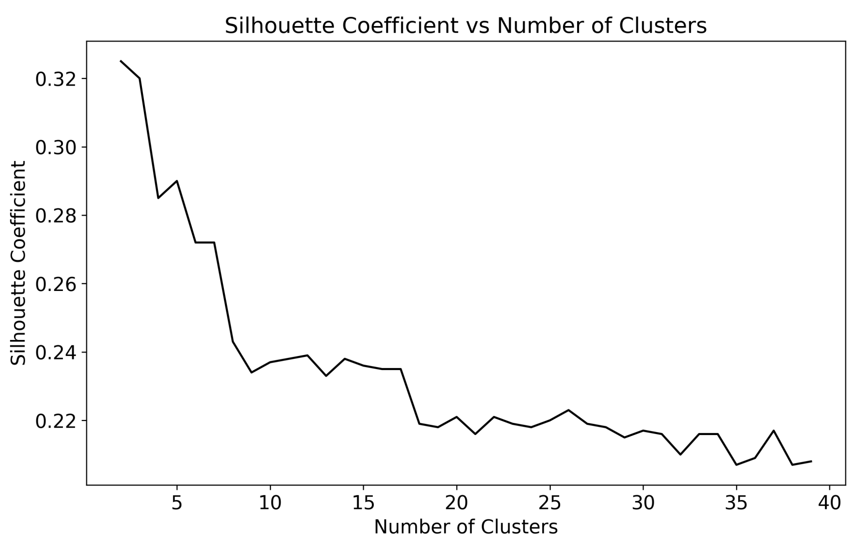


Figure 3.6: Number of clusters using the silhouette coeffecient

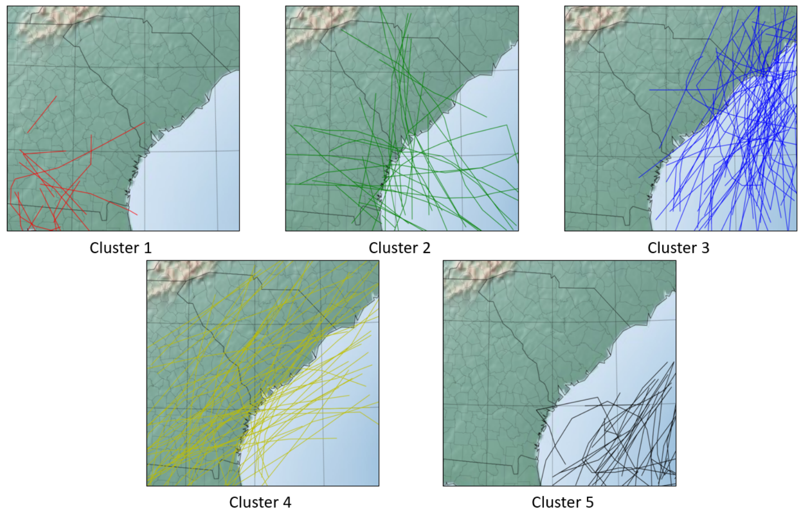


Figure 3.7: Final clusters after k-means clustering

Once the clusters are finalized, the number of hurricanes in a cluster are used to calculate the probability of a cluster. Five hurricane tracks are selected from a cluster as representative of the cluster each with an equal probability. The selection of representatives from a cluster is made from a list ordered by increasing distance from the cluster centroid. Since being closer to a centroid does not mean that a track has a greater probability of occurrence, tracks at list position: first track, 2/5*(list length), 3/5*(list length), 4/5*(list length) and last track are selected. Therefore, a total of 5 tracks are selected for each cluster, leading to a total of 25 possible tracks. Out of these 25 tracks, only seven tracks impacted the potential IMT and shipper/customer nodes. It was assumed that the area impacted by a hurricane is 100 miles, based on this the 18 tracks were assigned to 'No Impact' (NI) track category.

The probability of the representative tracks is calculated using the equation below,

$$\mathbb{P}[\text{Track Y}] = \frac{1}{5} \times \left(\frac{\text{No. of storms in parent cluster of Track Y}}{\text{Total no. of storms}} \right)$$

Therefore a total of eight track categories were developed to represent the possible hurricane scenarios/tracks: Track 1, Track 2, Track 3, Track 4, Track 5, Track 6, Track 7 and No Impact.

Table 3.5 below shows the probability calculation for each of the tracks. Figure 3.8 below shows the possible hurricane tracks and locations impacted within 100 miles.

Table 3.5: Hurricane tracks and related parameters

Parameters	Values by Track Categories							
	NI	T1	T2	T3	T4	T5	T6	T7
Parent Cluster Size	NA	31	31	31	74	54	54	54
Probability	0.73	0.03	0.03	0.03	0.06	0.04	0.04	0.04

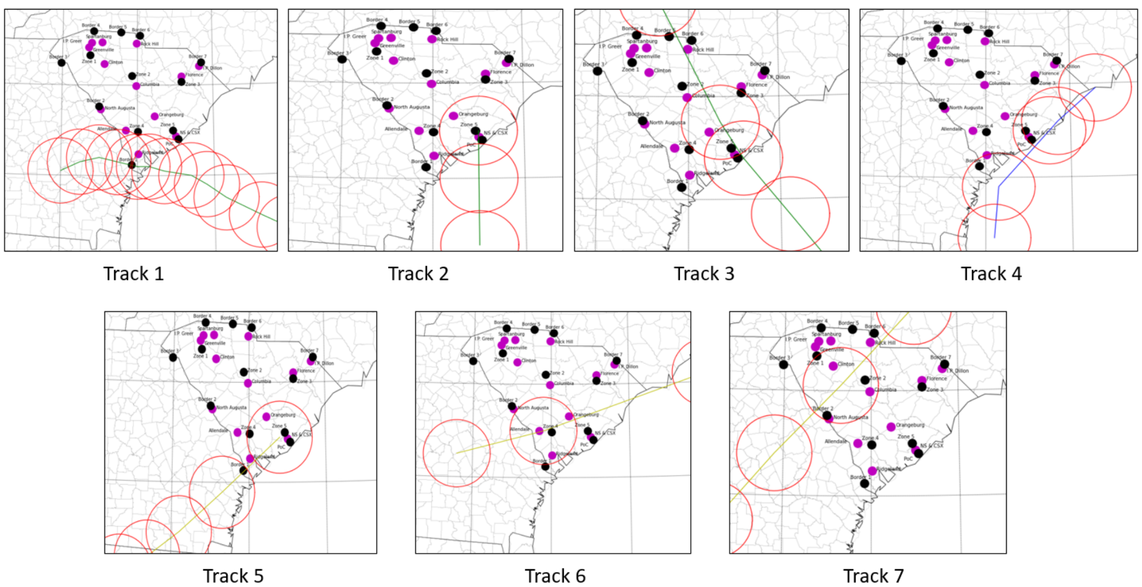


Figure 3.8: All possible hurricane tracks generated for the case study, the magenta circles represent potential IMT locations and black circles represent shippers/customers

Finally a scenario is defined as (Strength Category, Track Category) and the associated probability is calculated by assuming that these two are mutually independent events. The scenarios which have 'NH' strength or 'NI' track are collectively aggregated to a single scenario called 'No Disruption' (ND). This leads to a total of 36 scenarios with given disruption days and disruption locations. The equation used for probability calculation of a scenario is as follows,

$$\mathbb{P}[(\text{Cat X, Track Y})] = \mathbb{P}[\text{Cat X}] \times \mathbb{P}[\text{Track Y}]$$

The shippers' supply and IMTs' throughput for a quarter after disruption by a Cat X is calculated by using the following equations,

$$\text{Disrupted Supply} = \left(1 - \frac{\text{Disruption days for Cat X}}{90}\right) \times \text{Undisrupted Supply}$$

$$\text{Disrupted IMT Throughput} = \left(1 - \frac{\text{Disruption days for Cat X}}{90}\right) \times \text{Undisrupted IMT Throughput}$$

The two-stage stochastic model herein after is referred to as stochastic model and the model without uncertain parameters is referred to as deterministic model. The deterministic model's comparison is made with stochastic model so as to calculate the Value of Stochastic Solution (VSS). Deterministic model has no information of disruptions and makes all location and freight flow decisions assuming no future disruptions, while if disruptions were to happen the solution might not be optimal.VSS tests this deterministic solution against all expected scenarios to calculate the true long-term cost of using deterministic model against disruptions. VSS quantifies the long-term benefit of using stochastic model against deterministic model or the long-term savings a decision maker will make by using stochastic model solution instead of a deterministic model solution.

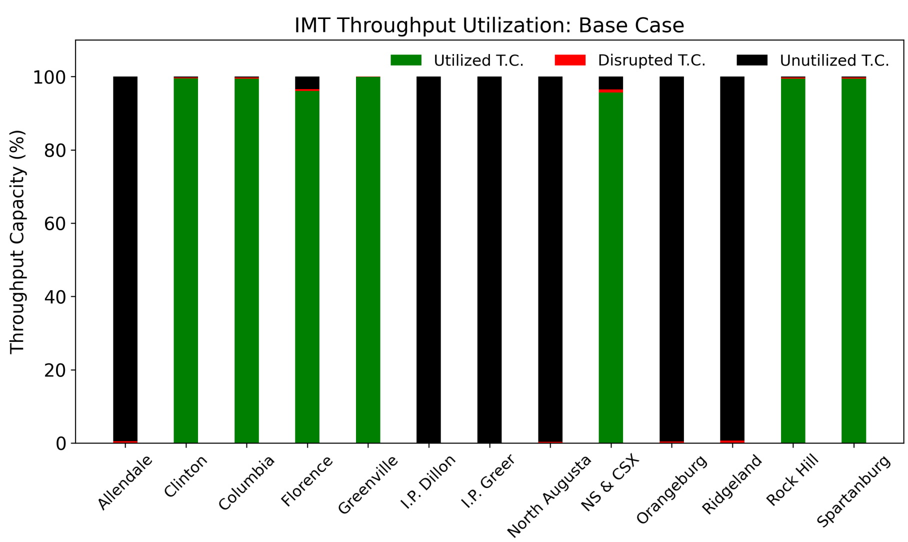


Figure 3.9: Expected IMT Utilization for Base Case: Stochastic and Deterministic Model

The results from deterministic and stochastic model both lead to same selected IMT locations. A total of seven locations selected are: Clinton, Columbia, Florence, Greenville, NS & CSX, Rock Hill, Spartanburg. Therefore, VSS is $0 for this case herein after referred to as the Base Case (BC). The stochastic model does not change selected IMT locations to counter disruptions since the disruptions at IMTs are not that significant and is evident from Figure 3.9. Moreover, since the disruptions are only in one quarter changing the IMT locations changes optimal freight flows in other three undisrupted quarters. Therefore, model decides to direct ship the small amount of freight which otherwise would have utilized the disrupted throughput at IMTs.

The base case uses past hurricane data and provides the managerial insight that the selected IMT locations from deterministic solution are resilient to disruptions and would still lead to an optimal solution. Although, it is recommended to use stochastic model since it helps you prepare for future disruptions as the decision makers are available with freight distribution plans for all the possible scenarios. Sensitivity Analysis is performed to show the impact of increased disruption and increased direct shipping cost on IMT selection. These additional cases also showcase the benefit of using a stochastic model.

3.5.3 Impact of Disruption Magnitude

The magnitude of disruptions is increased by changing the probability of scenarios to equally likely, and increasing the number of disruption days for all category hurricanes. Two set of experiments are performed: (1) Equally Likely Scenario-Medium Disruption (ELS_MD), (2) Equally Likely Scenario-High Disruption (ELS_HD). The disruption days by disruption cases are shown in Table 3.6 . For ELD_HD experiments the disruption can extend from Aug-Oct quarter to Oct-Dec quarter. The expected disruption days at potential IMT locations is shown in Figure 3.10 for BC, ELS_MD and ELS_HD.

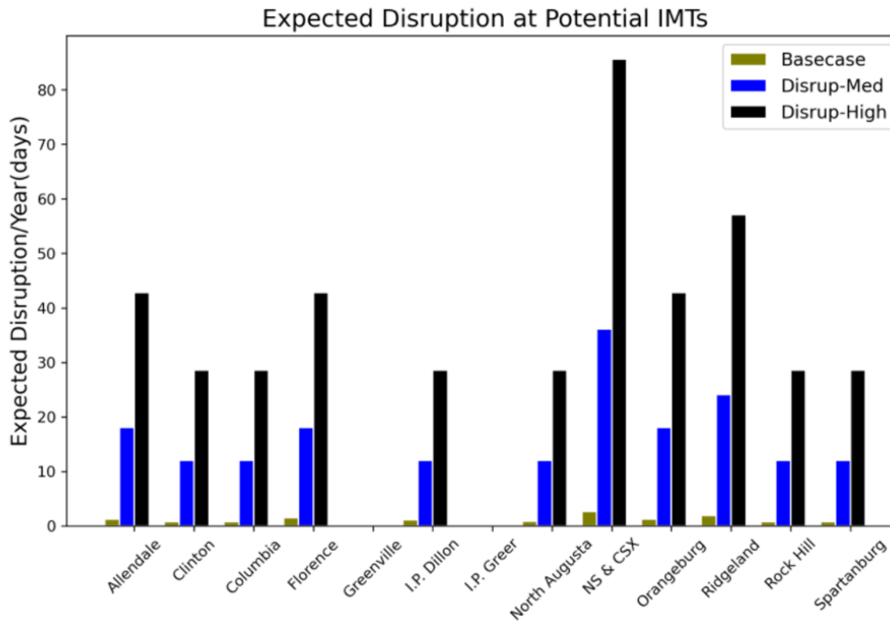


Figure 3.10: Expected Disrupted days at IMTs for Base Case, ELS_MD and ELS_HD experiments

Table 3.6: Disruption Duration used for sensitivity analysis

Experiment	Disruption duration (days)					
	NH	TS	H1	H2	H3	H4
ELS_MD	0	14	21	30	60	90
ELS_HD*	0	(30,0)	(60,0)	(90,0)	(90,60)	(90,90)

* Disruptions days in two quarters: (Aug-Oct, Nov-Jan)

The results show for ELS_MD case, the number of IMT opened are increased to eight as shown in Table 3.7. Figure 3.11 shows the expected IMT throughput utilization for both deterministic solution and stochastic solution against the disruption scenarios. Stochastic model opens an additional facility at Inland Port of Greer, which is not disrupted by any of the scenarios. Therefore, an extra undisrupted location is opened by spending more budget for additional IMT throughput capacity. This reduces the expected shipping cost by utilizing the cheaper intermodal shipping. For deterministic solution, NS & CSX faces more disruption and other opened IMTs are already working at full throughput capacity. Therefore the intermodal network capacity is reduced which although has a lower fixed cost, spends more on expensive direct shipping in long-term. The deterministic model leads to an increased long-term shipping cost and a VSS of $1.6M as shown in Table 3.7.

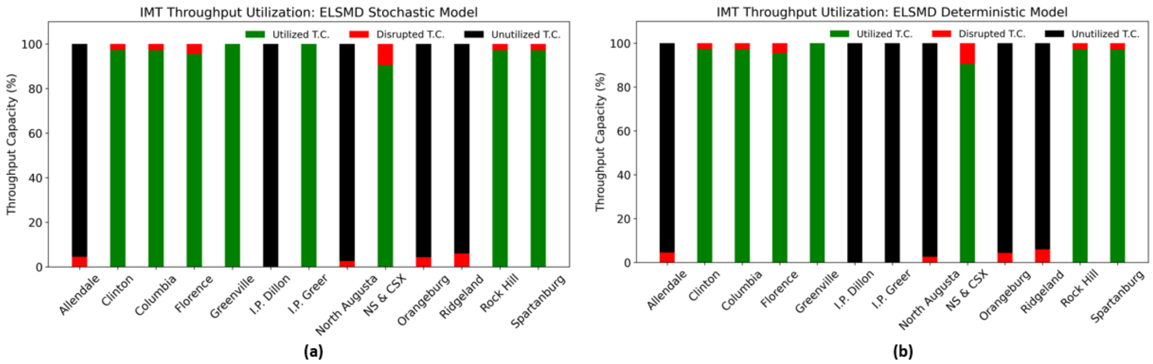


Figure 3.11: Expected IMT Utilization for ELS_MD using (a) Stochastic Model, and (b) Deterministic Model

For ELS_HD case, the number of IMTs opened are reduced to six as shown in Table 3.7. NS & CSX and Spartanburg IMTs are closed, which from Figure 3.12 is evident are disrupted even more and lead to less available IMT throughput to be utilized for same budget spent. Stochastic model trades these two highly disrupted IMT locations for an undisrupted IMT at Inland Port at Greer. The budget spent is reduced by $32M although expected shipping cost is increased. But this trade-off is justified when compared to deterministic solution, as it lead to a VSS of $5.5M (Table 3.7).

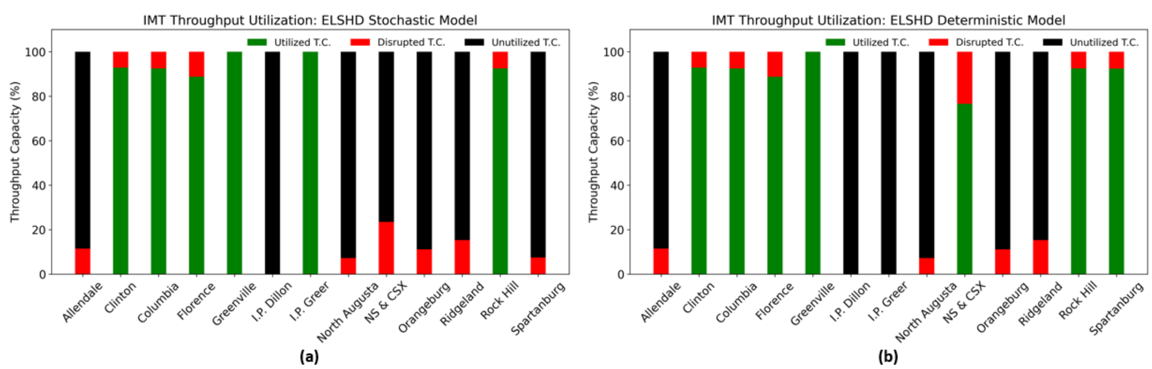


Figure 3.12: Expected IMT Utilization for ELS_HD using (a) Stochastic Model, and (b) Deterministic Model

Table 3.8 shows the solutions for stochastic model and deterministic model for the three experiments. The table values represent the dollars spent to ship a ton of freight through an IMT. It is evident that as disruption increases NS & CSX facility's cost/throughput increases by almost 10.5% for medium disruption and by 31% for high disruption. For medium disruption case, Spartanburg has 9.33M units of available throughput at \$3.71/unit, whereas IP Greer has 9.53M units of available throughput at \$4.10/unit therefore both are desirable locations. But as disruption increases to high, Spartanburg is left with 8.88M units of available throughput at \$3.89 whereas IP Greer has 9.53M units of available throughput at \$4.10/unit. Therefore model decides to close IMT at Spartanburg, and open an IMT at IP Greer for additional cheaper intermodal shipping.

Table 3.7: Sensitivity Analysis: Disruption Magnitude

Parameters	Experiment		
	Base Case	ELS_MD	ELS_HD
Potential IMTs			
Allendale			
Clinton	x	x	x
Columbia	x	x	x
Florence	x	x	x
Greenville	x	x	x
Inland Port of Dillon			
Inland Port of Greer		x	x
North Augusta			
NS & CSX North Charleston	x	x	
Orangeburg			
Ridgeland			
Rock Hill	x	x	x
Spartanburg	x	x	
Number of IMTs Opened	7	8	6
Budget Utilized(\$)	250M	289M	218M
Expected Variable Cost(\$)	0.95B	1.4B	2.32B
Expected Total Cost(\$)	1.19B	1.69B	2.54B
Value of Stochastic Solution(\$)	0	1.6M	5.5M

It is observed that NS & CSX and Spartanburg are important IMT locations for low cost shipping of freight between south-east region and upstate. As disruptions increase, NS & CSX due to its coastal location becomes highly prone and Spartanburg becomes relatively more prone to hurricane disruptions. Stochastic model spends extra budget by opening an additional IMT at

IP Greer to make-up for the lost IMT throughput capacity, while still utilizing the disrupted IMT at Spartanburg. But as disruption is increased further, NS & CSX is closed to avoid paying full fixed cost for a reduced capacity, and Spartanburg is traded with closely located IP Greer which has higher budget investment but more undisrupted capacity available.

Table 3.8: Fixed Cost Spent per Utilized Throughput for Opened IMTs

IMT Location	Fixed Cost Spent/Throughput Utilized ($/unit)						
	No Disruption	Base Case		ELS_MD		ELS_HD	
		Stochastic	Deterministic	Stochastic	Deterministic	Stochastic	Deterministic
Clinton	3.48	3.49	3.49	3.57	3.57	3.74	3.74
Columbia	4.08	4.11	4.11	4.20	4.20	4.41	4.41
Florence	3.78	3.93	3.93	3.95	3.95	4.25	4.25
Greenville	3.72	3.72	3.72	3.72	3.72	3.72	3.72
IP Greer*	NA	NA	NA	4.10	NA	4.10	NA
NS & CSX*	3.82	4.00	4.00	4.22	4.22	NA	4.99
Rock Hill	3.78	3.80	3.80	3.89	3.89	4.09	4.09
Spartanburg*	3.60	3.62	3.62	3.71	3.71	NA	3.89

* NA implies that an IMT is not a part of the solution for that experiment

3.5.4 Impact of Direct Shipping Cost

The methodology used till now only penalizes intermodal network in case of a disruption, but direct shipping is not affected. In case of disruptions the demand for trucks can increase critically leading to higher direct shipping costs. Therefore, it was necessary to study the effect of increased direct shipping cost on the intermodal network. The experiments performed in this section study the impact of both disruption magnitude and direct shipping costs on the IMT selection decisions and long-term benefits of using stochastic model. The direct shipping cost per unit is increased to 1.25 times, 1.5 times, and 2 times the base case direct shipping cost per unit and thus four st of experiments were performed for all three disruption cases.

Table 3.9 shows the IMT locations selected for each of the experiments performed by testing stochastic and deterministic solutions against all the scenarios. It is evident that as direct shipping costs increase, despite disruption of IMTs more IMTs are opened. When regular direct shipping cost is increased, the IMT locations selected are same across all the direct shipping cost cases irrespective of the type of disruption case. For base case, when direct shipping cost increases by 25% the VSS or the long-term savings increase drastically by $213M (Figure 3.13) and then keeps on increasing relatively steadily as direct shipping cost increases.

When medium and high disruption cases are compared to base case, the long-term savings decrease due to disruption of IMTs and is lowest for highly disrupted case. The reason being, IMTs are disrupted and thus not fully utilized, therefore need to pay full fixed cost of an IMT for cheaper intermodal shipping at reduced throughput capacity. For both medium and high disruption cases long-term savings increase non-linearly as direct shipping cost increases. For 25% increase in direct shipping cost VSS increases to 8.8 times for medium disruption and 2.56 times for high disruption case. Number of selected IMTs increase from six to eight for highest disruption case. Important locations of NS & CSX and Spartanburg are opened again in addition to IP Greer for highest disruption case. For further increase in direct shipping cost for medium and high disruption cases the VSS increases relatively steadily but at least to 2.5 times for any case.

It is observed in general that when direct shipping cost increases, number of IMT locations selected increase to achieve enough intermodal shipping capacity and avoid expensive direct shipping despite IMTs being disrupted.

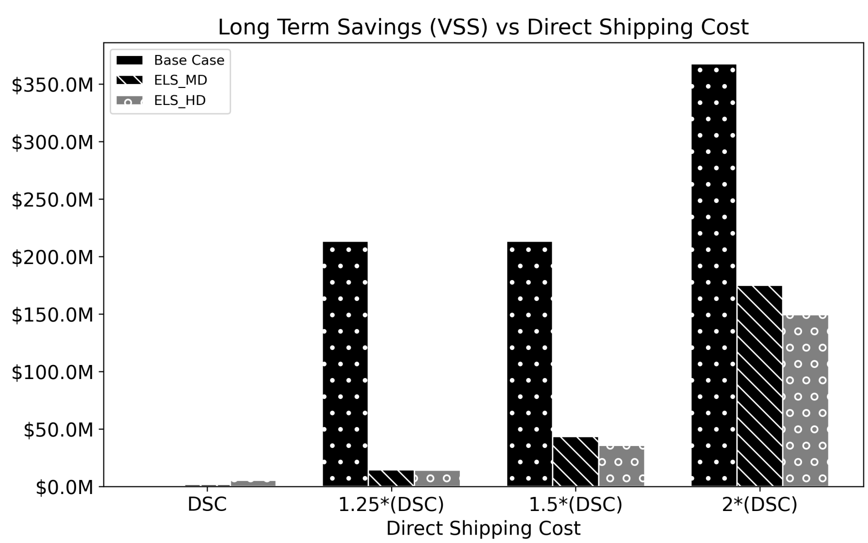


Figure 3.13: Value of Stochastic Solution for Different Direct Shipping Cost per unit by Disruption Intensity

Table 3.9: Sensitivity Analysis: Impact of Direct Shipping Cost per unit

Potential IMTs	Experiment											
	Base Case				ELS_MD				ELS_HD			
	1x	1.25x	1.5x	2x	1x	1.25x	1.5x	2x	1x	1.25x	1.5x	2x
Potential IMTs												
Allendale				x				x				x
Clinton	x	x	x	x	x	x	x	x	x	x	x	x
Columbia	x	x	x	x	x	x	x	x	x	x	x	x
Florence	x	x	x	x	x	x	x	x	x	x	x	x
Greenville	x	x	x	x	x	x	x	x	x	x	x	x
Inland Port of Dillon				x				x				x
Inland Port of Greer		x	x	x	x	x	x	x	x	x	x	x
North Augusta			x	x			x	x			x	x
NS & CSX North Charleston	x	x	x	x	x	x	x	x		x	x	x
Orangeburg			x	x			x	x			x	x
Ridgeland				x				x				x
Rock Hill	x	x	x	x	x	x	x	x	x	x	x	x
Spartanburg	x	x	x	x	x	x	x	x	x	x	x	x
Number of IMTs Opened	7	8	10	13	8	8	10	13	6	8	10	13
Budget Utilized(Million $)	250	289	360	471	289	289	360	471	218	289	360	471
Expected Variable Cost(Billion $)	0.94	1.07	1.15	1.26	1.4	1.56	1.63	1.73	2.32	2.40	2.47	2.57
Expected Total Cost(Billion $)	1.19	1.36	1.52	1.73	1.69	1.18	2.00	2.20	2.54	2.69	2.83	3.04
Value of Stochastic Solution(Million $)	0	213	238	368	1.65	14.5	43.5	175	5.51	14.1	35.9	149

3.6 Conclusions

This study presented an IMT location problem under facility disruptions. The disruption may occur at shipper or/and intermodal terminals. The model makes strategic decisions of IMT locations and number of IMTs to be opened so that freight distribution operations are resilient against any disruption scenario in long-term. Using such a model for disruption prone intermodal networks may lead to long-term savings. Level decomposition is used for solving this NP-hard problem. It is shown that it has a clear computational advantage against the L-shaped method and the extensive form.

A case study is performed for the state of South Carolina under hurricane disruptions to demonstrate the application of the model and validate results. The disruptions depend on the strength/category and track of the hurricane. k-means clustering is used to identify representative tracks. These representative tracks and category/strength data are used to generate a scenario. The model provides IMT location and freight routing decisions which minimizes the expected total cost against all the possible scenarios. The base case does not show any long-term savings, but an increase in disruption shows advantage of stochastic model over deterministic model by providing long-term savings. When further direct shipping costs are increased representing the increased demand for direct shipping the long-term savings from the stochastic model become even more prominent. The increase in disruptions led to lower long-term savings for stochastic model but still significant to be used.

This study has a few assumptions and also can be extended for some future research. The study uses only recorded hurricane location coordinates over time to apply clustering technique, another approach could be to also consider the landfall category, humidity or some other dependent factors to cluster similar hurricanes. The study considers only the wind damage from hurricanes, a complex methodology needs to be developed further to account for infrastructure damages done by hurricane related rainfalls, storm surges or tornadoes. The hurricane strength degradation over its track could be modelled, by using some factor dependent on strength of hurricane. The magnitude and track of hurricane are assumed to be independent, detailed study is needed to develop, if any, a correlation. Direct shipping cost if deemed necessary can be considered as a stochastic parameter and varied according to disruption magnitudes. This will need a detailed correlation study between freight shipping costs by trucks and magnitude of a hurricane.

These observations lead authors to a conclusion that stochastic model must be used for areas prone to facility disruptions, and even more when direct shipping costs are affected. The study aims to fill in research gap of IMT location under disruptions, developing a novel holistic methodology for hurricane disruptions and using an algorithm which is computationally more efficient than traditionally used L-shaped method.

Chapter 4

Trailer Scheduling at a Multi-door Cross-Dock with Asynchronous Inbound Trailer Arrival Times

4.1 Introduction

A cross-dock terminal is a trans-shipment facility between shippers and customers used for consolidation of freight by destination and the process itself is known as cross-docking. Multiple less-than-truckload (LTL) freight shipments to a destination leads to wasted truck capacity. This further leads to problems like higher transportation costs, increased traffic, and environment pollution. An example of such shipments is e-commerce, where customers order in smaller batches, more frequently and desire faster deliveries. Freight consolidation along with fast transshipment and no or short-term inventory can effectively solve this problem. Cross-docking is precisely built on this principle where freight from an inbound trailer is (1) unloaded, (2) sorted by destination, (3) transferred to a temporary storage area, and (4) then loaded on the destined outbound trailer.

Typically there is no storage or a very short-storage time at the cross-dock terminal leading to faster trans-shipments. Cross-docking creates additional material handling as compared to point-to-point deliveries, adding an extra trans-shipment time and material handling costs, but also eliminates operations like storage and retrieval as compared to a traditional warehouse [84]. According to Bartholdi et al. [17], cross-docking is economical if handling costs do not exceed transportation and inventory savings.

The operations at a cross-dock includes multiple elements and must be optimized to make the entire process efficient. The cross-dock operation optimization process may include tasks such as cross-dock shape selection, truck scheduling, resource management (e.g. labor, equipment), yard optimization, freight transfer (manual or automated), etc. The shape of a cross-dock determines the docking capacity of a cross-dock and flow of material inside the cross-dock. Truck scheduling problem requires synchronization between inbound and outbound trailer scheduling to achieve fast trans-shipments [78]. Inefficient synchronization can lead to delays in outbound trailer departures, unavailability of dock doors and increased storage at cross-dock thus leading to congestion and delayed freight transfers.

The allocation of resources like forklifts or labor on dock doors decides the unloading/loading time of the freight and freight transfer time between dock doors. The transfer of freight from inbound trailer to outbound trailer can be automated or manual. Automated transfer is more suitable when information about freight handled is known and/or is homogeneous and is faster. Manual transfers using forklifts are slower and can be used when either is not applicable or if decided by the decision makers.

The focus of this study is on truck scheduling for multiple dock doors. The synchronization of inbound and outbound trailer scheduling depends on operational decisions at cross-dock and information exchange between cross-dock operator and carriers. Operational decisions of truck-to-door assignment and trailer scheduling are very critical towards achieving efficient cross docking as they lead to faster trans-shipments and lower storage.

Information exchange is also one of the critical elements towards successful implementation of cross-docking. Particularly, when there is uncertainty in arrival times of trailers the entire optimized operations can be jeopardized. An online/real time decision making can be useful in such cases where carriers update the cross-dock about the change in arrival time and the cross-dock takes a recourse or makes adjustments to the operations and also informs the carriers about the updated schedule. Therefore, both are important elements in optimization of operations at cross-dock and information exchange can be included in decision making when arrival times are scattered and uncertain. Although information exchange is not a part of this study, but for our future study we aim to include information exchange.

4.2 Literature Review

The operations at a cross-dock facility typically include trailer docking, unloading, loading, and transfer of freight and depend on the cross-dock. The characteristics of a cross-dock are well studied by Belle et al.[78]. They study physical, operational and flow characteristics of a cross-dock as well as related cross-dock problems. The operational characteristics and different door environments are also studied comprehensively by Boysen et al. [22] but they also provide a detailed review of cross-dock scheduling problems and areas of improvement. Agustina et al. [6] present a review of the mathematical modeling approaches used for cross-dock planning at operational, technical and strategic levels. They cover various problems like scheduling, door assignment, product allocation, vehicle routing and transshipment. A cross-dock's shape (I, T, L, H, or X) can be selected based on the size (number of doors) of a cross-dock. The shape impacts operational factors like door utilization, and freight flows inside a cross-dock. A comprehensive study on cross-dock terminal shapes and its impact on factors like freight flows and labor costs is done by Bartholdi et al., [17]. The study also makes recommendations on shape selection based on number of docking doors and existing cross-dock expansions.

Synchronization of local cross-dock operations with inbound and outbound carrier network is important to achieve fast freight trans-shipments without storage or minimal and short period of storage. For e.g. a change in arrival time of inbound trailer due to breakdowns or traffic can lead to sub-optimal scheduling. The synchronization should be aimed at strategic, operational as well as tactical level of decisions making. Buijs et al. [24] present the framework needed for a synchronized cross-dock networks by identifying inter-dependencies of design, planning and scheduling of a cross-dock and its carrier network. This study identifies one of critical operational aspects of arrival time and scheduled time information exchange between cross-dock and carriers to develop an online problem for uncertain arrival times.

The real world operations at a cross-dock should be identified to make relevant assumptions in the related research work. Ladier et al. [49] presented a comparison between industry practices and literature to identify the gap for future research areas. This study aims to fill certain gaps in identified areas like departure deadlines for outbound trailers, handling of uncertain data, and fast solution of problems. A key study on improving cross-docking effectiveness was done by Apte et al. [9]. They present cases where cross-docking implementation can be suitable and cases where it is not desirable. They also provide guidelines for improvement of efficiency through design of information flow, and simulation.

The literature relevant to this study is discussed in the following review. We include in this section the literature that studies cross-docking problem in a post-distribution setting (interchangeable products). In such a setting an outbound trailer's demand for a product type can be satisfied by any inbound trailer with available supply for that product type. According to Boysen et al.[22], this allows more flexibility against uncertainty. Such a problem apart from truck scheduling must also optimize the demand allocation, which leads to an even more computationally challenging problem.

The seminal study in this research area was done by Yu et al. [84]. They studied this problem for a cross-dock with single strip door (unloading dock door) and single stack door (loading dock door). The arrival time of inbound trailers are assumed to be zero and temporary storage is allowed. They developed multiple constructive heuristics based on three strategies for selection of inbound trailers for demand satisfaction of an outbound trailer and three strategies for selection of outbound trailer to be scheduled next. The different combination of selection strategies are used to develop nine heuristics to minimize the make-span or the departure time of the last outbound trailer leaving the cross-dock. The compound heuristic selects the best solution out of these nine individual heuristics.

4.2.1 Single Stack Door and Single Strip Door Cross-dock Literature

Most of the studies have been performed for single strip door and single stack door problem, and the following literature review presents the relevant studies. Vahdani et al. [77] study this problem using flow time as a performance measure with a few modifications to the problem presented by Yu et al. [84]. They assume no temporary storage and preemption of trailers i.e. a trailer can partially load/unload, move out of a docking door and again dock to finish loading/unloading. Heuristics developed by Yu [83] are used to compare the performance of Tabu Search (TS), Genetic Algorithm (GA), and Electromagnetism-like algorithm (EM) with heuristic solutions as starting solutions. Later, Taguchi method is used to identify robust hyperparameter settings for the meta-heruistics. Arabani et al. [11] minimize a composite weighted objective function of earliness and tardiness. The underlying cross-dock features are based on Yu [83] and Yu et al. [84]. Just-in-time philosophy is followed to schedule trailers near due date and the solution methodology compares three robust meta-heuristics: GA, Particle Swarm Optimization (PSO), and Differential Evolution

(DE).

Forouharfard et al. [36] propose robust Imperialist Competitive Algorithm (ICA) with the objective of minimizing the number of products that pass through the temporary storage. The algorithm is compared with robust GA for solution quality in same computation time. Boysen et al. [23] present a decomposition approach under very simplified assumptions and some make-span lower bounds. The decomposed problem uses a fixed sequence for inbound scheduling problem and a bounded dynamic programming approach or heuristic start procedure to solve the outbound problem to find near optimal solutions.

Arbani et al. [10] propose a multi-objective problem aiming at minimizing the make-span and total lateness (or tardiness) of all outbound trailers. The solution methodology compares three multi-objective algorithms non-dominated sorting genetic algorithm-II, strength Pareto evolutionary algorithm-II and sub-population genetic algorithm-II against four performance measures (Hyper-area measure, spacing measure, mean ideal distance measure, and rate of achievement to two objectives simultaneously measure) for quality of solutions and performance.

Liao et al. [51] propose two hybrid DE meta-heuristics and a modification to the strategy/policy developed by Yu et al. [84]. The hybrid DE improved the computational efficiency as compared to the use of traditional DE proposed by Arbani et al. [11]. Keshtzari et al. [47] propose a mixed integer programming (MIP) based formulation for the problem and propose a solution approach which uses robust PSO hybridized with simulated annealing. (SA). The solution methodology is compared against GA and EM for computation time and solution quality.

4.2.2 Multi-Door Cross-dock Literature

The literature on multi-door cross-dock truck scheduling problem in a post-distribution setting are very limited and the following review presents the relevant studies. Liao et al. [52] studies this problem with an objective of minimizing total weighted tardiness. This study assumes outbound trailers are assigned fixed destinations, and thus only focuses on inbound trailer sequencing problem. Six meta-heuristics are proposed including SA, TS, Ant Colony Optimization, DE, and two hybrid DE. The meta-heuristics are compared for solutions quality and solution time. Tootkaleh et al. [73] studies this problem under a slight modification. The cross-docking assumes no product interchangeability under normal circumstances but allows for post-distribution concept for delayed loads. The delayed loads can be stored and dispatched on the next outbound trailer with same destination. They propose a MIP based model with an objective to minimize total delayed loads. This study also focuses only on inbound trailer scheduling by assuming destination exclusive stack doors and outbound trailers dedicated to a destination. A heuristic is proposed which produces good quality results and is faster than commercial solver w.r.t. solution time. Assadi et al. [14] proposes a just-in-time truck scheduling approach for scattered inbound and outbound trailer arrival times. They minimize the earliness and tardiness of both inbound and outbound trailers and propose DE and population based simulated annealing (PBSA) meta-heuristics. The demand allocation or product flows are determined using first-come first-served policy.

The contribution towards studying new cross-dock scheduling problems and multi-door cross-docking are limited. Thus this paper aims at filling that research gap by studying a new problem, and proposing appropriate MIP based mathematical model, and solution methodology. We study a multi-door cross-dock truck scheduling problem with scattered inbound trailer arrival times. The objective of the problem is to minimize the make-span and total tardiness penalty of outbound trailers using a convex piece-wise linear penalty cost function. The non-linear penalty cost leads to larger penalty multipliers when tardiness is in a higher tardiness range. The penalty function allows different penalty costs for different trailers as well as optimizes the trade-off between higher tardiness on a single outbound trailer or small tardiness on multiple outbound trailers. Smaller tardiness (e.g. 1 hour) maybe acceptable for an outbound carrier as they might be able to make up for lost time by re-optimizing the freight routes. Moreover, we extend the strategy proposed by Yu et al. [84] to develop a heuristic for multi-door problem and use the heuristic solution as a solution for PBSA meta-heuristic as well as generating demand allocations for new solutions generated in PBSA iterations.

The rest of the study is arranged as follows. Section 4.3 describes the problem studied including the assumptions made and presents the mathematical model. Section 4.4 presents the computation results, and impact of key input parameters on performance measures. Finally, in section 4.5 we summarize the key highlights of this study and future research areas.

4.3 Problem Description and Methodology

This study determines the operational decisions of cross-duck scheduling for a multi-door cross-dock handling multiple product types while minimizing the sum of make-span and total tardiness of outbound trailers. The problem given a set of inbound trailers and associated arrival times, set of outbound trailers and associated departure deadlines, products loaded on inbound and needed on outbound trailers, set of inbound and outbound dock doors determines the docking schedule and door assignment of inbound and outbound trailers as well as product assignments. The study makes several assumptions and are defined as follows:

1. Inbound trailers arrive at cross-dock throughout the planning horizon (asynchronous arrivals).
2. Outbound trailers are available at the cross-dock at the start of planning horizon.
3. Cross-dock docking doors are exclusive for loading (strip door) and unloading (stack door) operations.
4. Outbound trailers must be loaded with the products needed (a priori), and can use any inbound trailer's load (products are interchangeable).
5. For each product number of units needed on outbound trailers is equal to the number of units loaded on inbound trailers.
6. Outbound trailers have a soft deadline, after which any tardiness (delay past deadline) is penalised depending on the destination and magnitude of tardiness.
7. Transshipment time between a strip door and stack door is directly proportional to distance between the given pair of doors.
8. Preemption (i.e. undocking a trailer inbetween loading/unloading and dock again for complete loading) is not allowed.
9. Each product has an associated unloading/loading time.
10. Cross-dock has unlimited temporary storage (storage must be emptied by end of planning horizon.
11. The products are unloaded from inbound trailer, sorted by destined outbound trailer, transferred to temporary storage in front of docking door of destined outbound trailer.
12. A product is available for unloading from an inbound trailer at an average, half the sum of total unloading time for all the loaded products.

13. Manual transfer of freight (e.g. forklifts) and unconstrained freight flow between docking doors.

14. Products can be loaded on an outbound trailer from different inbound trailers in parallel, vice versa for inbound trailers.

15. At each docking door, between any two docking there must be a minimum time period known as truck changeover time.

The study also assumes a non-linear penalty function for tardiness of an outbound trailer, which penalizes higher for higher tardiness values. As shown in Figure 4.1 we use a piece-wise linear convex penalty function to model this feature. This allows decision makers to reduce higher tardiness on outbound trailers, possibly by accepting a smaller tardiness on other outbound trailer. Tardiness under a threshold value can be acceptable as the lost time can be covered by the outbound trailer (re-optimize the route). We assume two breakpoints (ϕ_1 and ϕ_2) and three pieces (linear functions) with slopes $\lambda_1 F_j$, $\lambda_2 F_j$, $\lambda_3 F_j$ to model this function for an outbound trailer $j \in T_O$ with penalty cost F_j , but can be extended for any number of pieces. If a convex function is known, a convex piece-wise linear approximation can be fitted and then this study is still applicable.

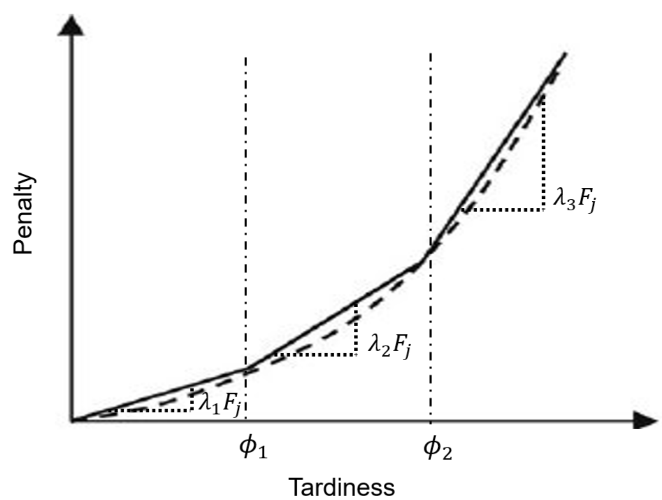


Figure 4.1: Convex piece-wise linear tardiness penalty function

In the following subsections for the given problem, we first develop a MIP based mathematical model, then we discuss a fast heuristic, and use it as a starting solution for Population Based Simulated Annealing (PBSA) as well as to construct product assignments for new solutions generated in PBSA.

4.3.1 Mathematical Model

A mixed integer non-linear programming based model is developed for the given problem, then is reformulated to a mixed integer linear programming model.

Notation

Sets

I	strip doors
O	stack doors
T_I	inbound trailers
T_O	outbound trailers
P	products

Parameters

H	end time of planning horizon (min)
A_i	arrival time of inbound trailer $i \in T_I$ at the cross dock terminal (min)
T_{kg}	transshipment time between strip door $k \in I$ and stack door $g \in O$ (min)
W_p	unloading/loading time for product $p \in P$ (min)
Q_j	departure deadline for outbound trailer $j \in T_O$ (min)
F_j	penalty factor for each unit of tardiness of an outbound trailer $j \in T_O$
C	trailer changeover time (\$/min)
S_{ip}	number of units of product $p \in P$ available from inbound trailer $i \in T_I$
D_{jp}	number of units of product $p \in P$ required by outbound trailer $j \in T_O$
M	big number (greater than or equal to $\sum_{p \in P} D^i_{jp}$)
ϕ_1, ϕ_2	break points for the convex piece-wise linear function (min)
$\lambda_1, \lambda_2, \lambda_3$	penalty multipliers for the convex piece-wise linear function

---

Decision Variables

e_{ik}^I arrival time of inbound trailer $i \in T_I$ at strip door $k \in I$ (≥ 0)

l_{ik}^I leave time of inbound trailer $i \in T_I$ from strip door $k \in I$ (≥ 0)

e_{jg}^O entry time of outbound trailer $j \in T_O$ at stack door $g \in O$ (≥ 0)

l_{jg}^O leave time of outbound trailer $j \in T_O$ from stack door $g \in O$ (≥ 0)

$l_{\max}$ make-span or leave time of the last departing outbound trailer (≥ 0)

γ_j tardiness of outbound trailer $j \in T_O$ (≥ 0)

r_{ij}^p number of units of product $p \in P$ transferred from inbound trailer $i \in T_I$ to outbound trailer $j \in T_O$ (≥ 0 and Int)

$$\alpha_{iq}^k = \begin{cases} 1, & \text{if inbound trailer } i \in T_I \text{ precedes inbound trailer } q \in T_I \text{ at strip door } k \in I \\ 0, & \text{otherwise} \end{cases}$$

$$\beta_{jr}^g = \begin{cases} 1, & \text{if outbound trailer } j \in T_O \text{ precedes inbound trailer } r \in T_O \text{ at stack door } g \in O \\ 0, & \text{otherwise} \end{cases}$$

$$x_{ik} = \begin{cases} 1, & \text{if inbound trailer } i \in T_I \text{ is assigned to strip door } k \in I \\ 0, & \text{otherwise} \end{cases}$$

$$y_{jg} = \begin{cases} 1, & \text{if outbound trailer } j \in T_O \text{ is assigned to stack door } g \in O \\ 0, & \text{otherwise} \end{cases}$$

$$v_{ij}^{kg} = \begin{cases} 1, & \text{if freight is transferred from inbound trailer } i \text{ at door } k \text{ to outbound trailer } j \text{ at door } g \\ 0, & \text{otherwise} \end{cases}$$

Convex Piece-wise Linear Penalty Function $f(\gamma_j)$

$$f(\gamma_j) = \begin{cases} (\lambda_1 F_j)\gamma_j, & 0 \leq \gamma_j < \phi_1 \\ (\lambda_2 F_j)\gamma_j + \phi_1 F_j(\lambda_1 - \lambda_2), & \phi_1 \leq \gamma_j < \phi_2 \\ (\lambda_3 F_j)\gamma_j + \phi_1 F_j(\lambda_1 - \lambda_2) + \phi_2 F_j(\lambda_2 - \lambda_3), & \phi_2 \leq \gamma_j \end{cases} \tag{4.1}$$

$$\text{Minimize} \sum_{j \in T_O} f(\gamma_j) + \max_{\substack{j \in T_O, \\ g \in O}} \{l_{jg}^O\} \tag{4.2}$$

Subject to,

$$\sum_{k \in I} x_{ik} = 1 \qquad \forall i \in T_I \tag{4.3}$$

$$\sum_{g \in O} y_{jg} = 1 \qquad \forall j \in T_O \tag{4.4}$$

$$e_{ik}^I \geq x_{ik} A_i \qquad \forall i \in T_I, k \in I \tag{4.5}$$

$$l_{ik}^I - e_{ik}^I \geq x_{ik} \left(\sum_{p \in P} S_{ip} W_p \right) \qquad \forall i \in T_I, k \in I \tag{4.6}$$

$$e_{qk}^I \geq C + l_{ik}^I - H \left(1 - \alpha_{iq}^k\right) \qquad \forall i, q \in T_I : i \neq q, k \in I \tag{4.7}$$

$$\alpha_{iq}^k + \alpha_{qi}^k \geq x_{ik} + x_{qk} - 1 \qquad \forall i, q \in T_I : i \neq q, k \in I \tag{4.8}$$

$$\alpha_{iq}^k + \alpha_{qi}^k \leq 1 \qquad \forall i, q \in T_I : i \neq q, k \in I \tag{4.9}$$

$$\alpha_{ii}^k = 0 \qquad \forall i \in T_I, k \in I \tag{4.10}$$

$$e_{rg}^O \geq C + l_{jg}^O - H \left(1 - \beta_{jr}^g\right) \qquad \forall j, r \in T_O : j \neq r, g \in O \tag{4.11}$$

$$\beta_{jr}^g + \beta_{rj}^g \geq y_{jg} + y_{rg} - 1 \qquad \forall j, r \in T_O : j \neq r, g \in O \tag{4.12}$$

$$\beta_{jr}^g + \beta_{rj}^g \leq 1 \qquad \forall j, r \in T_O : j \neq r, g \in O \tag{4.13}$$

$$\beta_{jj}^g = 0 \qquad \forall j \in T_O, g \in O \tag{4.14}$$

$$\sum_{j \in T_O} \sum_{k \in I} \sum_{g \in O} r_{ij}^p \le S_{ip} \qquad \forall i \in T_I, p \in P \tag{4.15}$$

$$\sum_{i \in T_I} \sum_{k \in I} \sum_{g \in O} r_{ij}^p \ge D_{jp} \qquad \forall j \in T_O, p \in P \tag{4.16}$$

$$\sum_{p \in P} r_{ij}^p \le M \left(\sum_{k \in I} \sum_{g \in O} v_{ij}^{kg} \right) \qquad \forall i \in T_I, j \in T_O \tag{4.17}$$

$$v_{ij}^{kg} \le x_{ik} \qquad \forall i \in T_I, j \in T_O, k \in I, g \in O \tag{4.18}$$

$$v_{ij}^{kg} \le y_{jg} \qquad \forall i \in T_I, j \in T_O, k \in I, g \in O \tag{4.19}$$

$$l_{jg}^O \ge e_{ik}^I + \frac{\sum_{p \in P} S_{ip} W_p}{2} + T_{kg} + \sum_{p \in P} r_{ij}^p W_p - H \left(1 - v_{ij}^{kg}\right) \qquad \forall i \in T_I, j \in T_O, k \in I, g \in O \tag{4.20}$$

$$l_{jg}^O \ge e_{jg}^O + y_{jg} \left(\sum_{p \in P} D_{jp} W_p \right) \qquad \forall j \in T_O, g \in O \tag{4.21}$$

$$l_{jg}^O \le y_{jg} Q_j + \gamma_j \qquad \forall j \in T_O, g \in O \tag{4.22}$$

$$e_{ik}^I \le x_{ik} H \qquad \forall i \in T_I, k \in I \tag{4.23}$$

The objective function (4.2) is non-linear and minimizes the sum of make-span and total tardiness penalty of outbound trailers. The tardiness penalty for an outbound trailer is given by the convex piece-wise linear function (4.1). The objective function can be easily linearized by introducing additional variables for tardiness penalty and make-span and is presented next. Constraints (4.3) and Constraints (4.4) ensure that each inbound and outbound trailer is assigned to exactly one strip door and one stack door respectively. Constraints (4.5) ensure that an inbound trailer cannot be docked at a selected strip door before its arrival time. Constraints (4.6) ensure that an inbound trailer's service time (leave time - entry time) at assigned strip door should be greater than or equal to the unloading time for all the loaded products.

Constraints (4.7)-(4.10) are precedence constraints for inbound trailers at a strip door. If an inbound trailer 'i' precedes another inbound trailer 'q' at a strip door 'k', these set of constraints ensure that entry time of trailer 'q' at strip door 'k' is greater than or equal to the sum of leave time of trailer 'i' at strip door 'k' and the trailer changeover time. Constraints (4.11)-(4.14) are precedence constraints for outbound trailers at a stack door, and function exactly like constraints (4.7)-(4.10).

Constraints (4.15) are supply capacity constraints and ensure that total number of units of a product transferred from an inbound trailer to all outbound trailers does not exceed the total number of units available. (4.16) are demand satisfaction constraints and ensure that total number of units of a product transferred to an outbound trailer is greater than or equal to the number of demanded units. Constraints (4.17)-(4.19) are freight flow constraints and ensure that if any freight flow exists between an inbound trailer docked at a strip door 'k' and an outbound trailer docked at a stack door 'g', it should be routed through the designated freight transfer path between the strip door 'k' and stack door 'j'.

Constraints (4.20) and constraints (4.21) are service time constraints for an outbound trailer and ensure that an outbound trailer leaves the assigned stack door only after it has loaded all the demanded products w.r.t. the freight transfer from inbound trailers and its entry time at stack door respectively. Constraints (4.22) are soft deadline/tardiness constraints and ensure that if an outbound trailer's leave time from the assigned stack door is greater than the deadline, a penalty is paid. Constraints (4.23) ensure that no inbound trailer is scheduled after the end time of planning horizon.

Reformulating Non-Linear Model

The MIP model presented above has a non-linear objective function (4.2), and can be easily reformulated to a linear objective function by adding new variables and constraints. The formulation is presented below:

$$\text{Minimize} \sum_{j \in T_O} z_j + l_{\max} \tag{4.24}$$

$$z_j \geq (\lambda_1 F_j)\,\gamma_j \qquad \forall j \in T_O \tag{4.25}$$

$$z_j \geq (\lambda_2 F_j)\,\gamma_j + \phi_1 F_j\,(\lambda_1 - \lambda_2) \qquad \forall j \in T_O \tag{4.26}$$

$$z_j \geq (\lambda_3 F_j)\,\gamma_j + \phi_1 F_j\,(\lambda_1 - \lambda_2) + \phi_2 F_j(\lambda_2 - \lambda_3) \qquad \forall j \in T_O \tag{4.27}$$

$$l_{\max} \geq \sum_{g \in O} l^{O}_{jg} \qquad \forall j \in T_O \tag{4.28}$$

The resulting new MIP model has a linear objective function (4.24) and is subject to constraints (4.3)-(4.23) and constraints (4.25)-(4.28).

The non-preemptive truck scheduling problem in this study is an extension of problems studied earlier with single door, and single product. This problem also includes additional features like multi-product, multi-doors, product interchangeability, and soft-deadlines. Multiple studies have proven this problem to be NP-hard [21, 28, 73]. Therefore, a problem large instance is computationally hard to solve under a time limit fit for use in practical applications. Apart from that, for real-time/online application of this model the cross-dock operator must be able to make these decisions in a short-time. Therefore, we develop a fast constructive heuristic to produce good starting solution and then use Population Based Simulated Annealing (PBSA) meta-heuristic to improve the solution quality. The heuristic solution is also used to create product assignments for the new solutions created in the PBSA meta-heuristic.

4.3.2 Multi-Door Cross-Dock Heuristic (MDCDH)

Yu et al. [83, 84] developed a two-stage constructive heuristic for trailer scheduling in a cross-dock with single door (one strip door and one stack door). The demand and supply for each product is assumed to be balanced/equal. The inbound trailers are assumed to be present at cross-dock at start of planning horizon. The study identifies two kind of routes/flows in a cross-dock: (1) direct transfer from inbound trailer to outbound trailer, and (2) transfer through a temporary storage. The heuristics developed is based on the idea of maximizing the direct flow or minimizing the temporary storage.

The first stage created associated inbound trucks/trailers (AIT) for each outbound trailer. AIT for an outbound trailer can be defined as a sequence of subset of inbound trailers that can provide with all the products to be loaded. There could be multiple AIT/subsets but only one sequence is created if we use an inbound trailer selection strategy. The second stage selected an outbound trailer and the associated AIT to be scheduled next based on an outbound trailer selection strategy. This process is repeated iteratively till all the outbound trailers are scheduled. A total of three selection strategies were developed for inbound and outbound trailers each based on minimizing storage. The combinations of different strategies at each stage led to a total of nine heuristic algorithms.

The results indicate the best heuristic strategies are: (1) First stage: For creating AIT select an inbound trailer that creates minimum storage/unloading time, (2) Second stage: select outbound trailer whose AIT create minimum storage/unloading time. Therefore, we select this policy with a few adjustments and develop a Multi-Door Cross-Dock Heuristic (MDCDH) for cross-dock scheduling problem with multiple doors and asynchronous inbound trailer arrivals. The MDCDH is explained as follows.

4.3.2.1 First Stage

The products loaded (supply) on an inbound trailer that cannot be direct transferred to an outbound trailer are placed in the temporary storage. For an unscheduled outbound trailers the products needed (demand) can be obtained either through temporary storage or direct transfer from an inbound trailer scheduled at a strip door. The temporary storage at the start of the planning horizon is empty. If at least one unit of demand is available in temporary storage at the time of outbound trailer's docking, the first available unit will be used first to satisfy the demand. The remaining demand will be satisfied using the unscheduled inbound trailers.

For each unscheduled outbound trailer we create a AIT or determine the product transfers. We only consider the unscheduled inbound trailers for creating AIT, as unused supply of an inbound trailer is considered as temporary storage. The AIT for an outbound trailer can be created using an iterative strategy. In each iteration we use the inbound trailer selection strategy to select one unscheduled inbound trailer. The termination criteria is sum of temporary storage and supply from AIT is greater than or equal to the demand of an outbound trailer for each product.

Inbound Trailer Selection Strategy: We use two measures to select an unscheduled inbound trailer in the iterative process of creating AIT: (1) Unloading time for excess supply, and (2) Earliest product availability time.

Unloading supply in excess of demand of the associated outbound trailer can lead to idle time at the strip door. This is calculated by using a foresight approach based on Yu et al. [83, 84]. The calculation however is not straightforward, the products remaining on the unscheduled inbound trailer after supplying its associated outbound trailer, can be used to satisfy the demand of unscheduled outbound trailers to be scheduled next at each stack door. Using this approach would lead to selection of inbound trailers which create storage only in short-term or temporary storage in real sense. This also prevents ignoring inbound trailers that can transfer products to its associated outbound trailer and other unscheduled outbound trailers to be scheduled immediately next at each stack door.

We denote unloading time for excess supply of an inbound trailer $i \in T_I$ in AIT of outbound trailer $j \in T_O$ by ES_{ij}, set of unscheduled outbound trailers by T_{UO} where $T_{UO} \subseteq T_O$, number of product $p \in P$ to be loaded on outbound trailer $j \in T_O$ after iteration 'iter' by D_{jp}^{iter}. The number of outbound trailers scheduled immediately after outbound trailer $j \in T_O$ are given by $\alpha = min(|O|, |T_{UO} \setminus j|)$. Finally, $T_{UO}^{\alpha} \subseteq T_{UO} \setminus j$ denotes the set of unscheduled outbound trailers ($|T_{UO}^{\alpha}| = \alpha$). Then ES_{ij} is given by equation 4.29.

$$ES_{ij} = min_{l \in T_{UO}^{\alpha}} \left(\sum_{p \in P} max(0, S_{ip} - D_{jp}^{iter} - \sum_{l \in T_{UO}^{\alpha}} D_{lp}) W_p \right) \tag{4.29}$$

A worked out hypothetical example is shown below to explain the calculation of unloading time for excess supply. Assume that the supply and demand of each unscheduled inbound and outbound trailer respectively is as given by Table 4.4 and unit unloading time $W_p = 1$ for both products. We show calculations for first iteration of creating AIT of outbound trailer-1 (OT-1).

Inbound Trailer	Product-1	Product-2
IT-1	12	15
IT-2	3	5

Outbound Trailer	Product-1	Product-2
OT-1	6	5
OT-2	4	8
OT-3	3	4
OT-4	2	3

Table 4.4: Product Loaded on Inbound Trailer (left) and Products to be Loaded on Outbound Trailer (right)

Unloading time for excess supply of IT-1:

α = min(2, 3) = 2, therefore possible combinations T_{UO}^{α} are {OT-2, OT-3}, {OT-3, OT-4}, and {OT-2, OT-4}.

$$\begin{aligned} ES_{11} =& min(max(0, 12 - 6 - (4+3)) * 1 + max(0, 15 - 5 - (8+4)) * 1, \\ & max(0, 12 - 6 - (3+2)) * 1 + max(0, 15 - 5 - (4+3)) * 1, \\ & max(0, 12 - 6 - (4+2)) * 1 + max(0, 15 - 5 - (8+3)) * 1) \end{aligned}$$

$$\implies ES_{11} = min(0, 4, 0) = 0$$

The product availability time is the earliest time products loaded on inbound trailer $i \in T_I$ are available for transshipment. Earliest product availability time takes into account the idle time created for an outbound trailer at a stack door. While waiting for an associated inbound trailer to arrive for product transfer, the outbound trailer occupies the stack door for a longer period of time. Therefore, it is preferred that products are available for loading on to the outbound trailer as soon as it enters the stack door. The product availability time (AT_i) for inbound trailer $i \in T_I$ is calculated using the equation 4.30.

$$AT_i = min_{k \in I}(e_{ik}^I) + \frac{\sum_{p \in P} S_{ip} W_p}{2} \tag{4.30}$$

Once both measures are available for each inbound trailer we calculate equally weighted sum of relative percentage deviations (RPD) of both measures, and select the inbound trailer with least value, or randomly in case of a tie. RPD is calculated using the equation 4.31.

$$\text{Relative Percentage Deviation (RPD)} = \left(\frac{\text{measure value-best measure value}}{\text{best measure value}}\right) * 100 \qquad (4.31)$$

4.3.2.2 Second Stage

The second stage receives information regarding outbound trailers and their associated inbound trailer from the first stage. Then an outbound trailer selection strategy is used to determine the which outbound trailer and its AIT will be scheduled next.

Outbound Trailer Selection Strategy: We again use two measures to determine the next scheduled outbound trailer and its AIT: (1) Departure time of an outbound trailer, and (2) Unloading time for excess supply of the AIT.

Departure time of an outbound trailer refers to the time an outbound trailers completes loading of all products needed and leaves the assigned stack door. Since we want to increase availability of stack doors at any given time, we want the outbound trailers to leave as soon as possible.

The second measure is sum of unloading time for excess supply of all the inbound trailers in the AIT. Minimizing unloading time for excess supply makes sure the availability of strip doors is increased. This is ensured as the inbound trailers in the AIT spend minimum time in unloading products not useful in the short-term.

In case, the departure time of one or more outbound trailers exceed deadline, the outbound trailer with highest tardiness is selected to be scheduled next. Otherwise, equally weighted sum of RPD for both measures is calculated, and an outbound trailer with the least value is selected. The outbound trailers and inbound trailers are scheduled at a door with earliest possible docking time, which is the minimum of arrival time and earliest available door time. In case of a tie, a door with lower idle time after the last scheduled trailer's leave time is selected.

A hypothetical example explaining the impact of idle time on scheduling is shown in Figure 4.2 and Figure 4.3. Assume we are scheduling IT-2 at a cross-dock with two strip doors. The arrival time of IT-2 is 'A', leave time of IT-4 at stack door-1 is 'B', truck changeover time is 'T.C.' and $B + T.C. < A$. In this case it is possible to schedule IT-2 at any strip door achieving the same entry time, but scenario in Figure 4.2 leads to wasted utilization or higher idle-time than scenario in Figure 4.3.

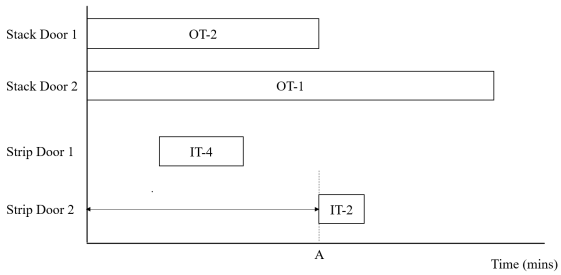


Figure 4.2: Strip door-2 idle time = A

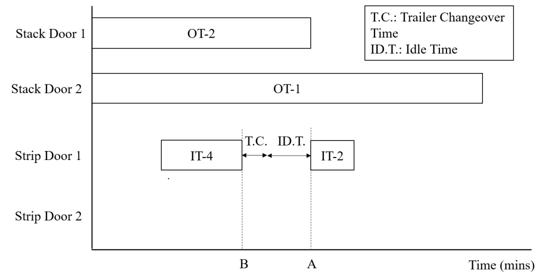


Figure 4.3: Strip door-1 idle time = (A - B - T.C)

The pseudo-code for the MDCDH Algorithm is presented in Appendix B.

4.3.3 Population Based Simulated Annealing

Simulated Annealing (SA) is a popular optimization algorithm that derives its inspiration from annealing of solids. SA was first developed by Kirkpatrick et al. [48] for combinatorial optimization problems. It is applicable to both continuous and discrete optimization problems and has been successfully implemented for solving large-scale problems in vast areas of application. The significant advantage of SA is that in contrast to greedy algorithms it also escapes local optima by accepting worse neighboring solutions (diversification) depending on a Boltzmann distribution. The Boltzmann distribution is a function of energy difference/absolute gap between two solutions, initial temperature and the cooling schedule. SA has been applied to cross-dock scheduling problems in post-distribution setting in studies including Liao et al. [52], and Keshtzari et al. [47].

Population based simulated annealing (PBSA) as opposed to using a single iteration solution it uses a population of neighboring solution to select the best recourse given the past decisions. Assadi et al. [14] applied PBSA for solving a multi-door cross dock scheduling problem. Neighbouring solutions are generated using pairwise swaps, and product flows are determined using first come first serve policy.

We propose PBSA that uses the MDCDH solution as a starting solution. At each iteration a population of neighborhood solutions is generated using pairwise swap and insert operations on the best solution from previous iteration. The product transfers, and outbound trailer departure times for neighborhood solutions are generated again using the inbound trailer selection strategy. The fitness of each objective function is compared and the best solution is retained for population generation in the next iteration (intensification). The best solution can lead to a lower or higher objective value. If current best solution is less than global best solution it is assigned as global best solution, else the worst solution is accepted with a probability given by Boltzmann distribution. The stopping criteria for the algorithm is maximum number of iterations, which is a predefined parameter.

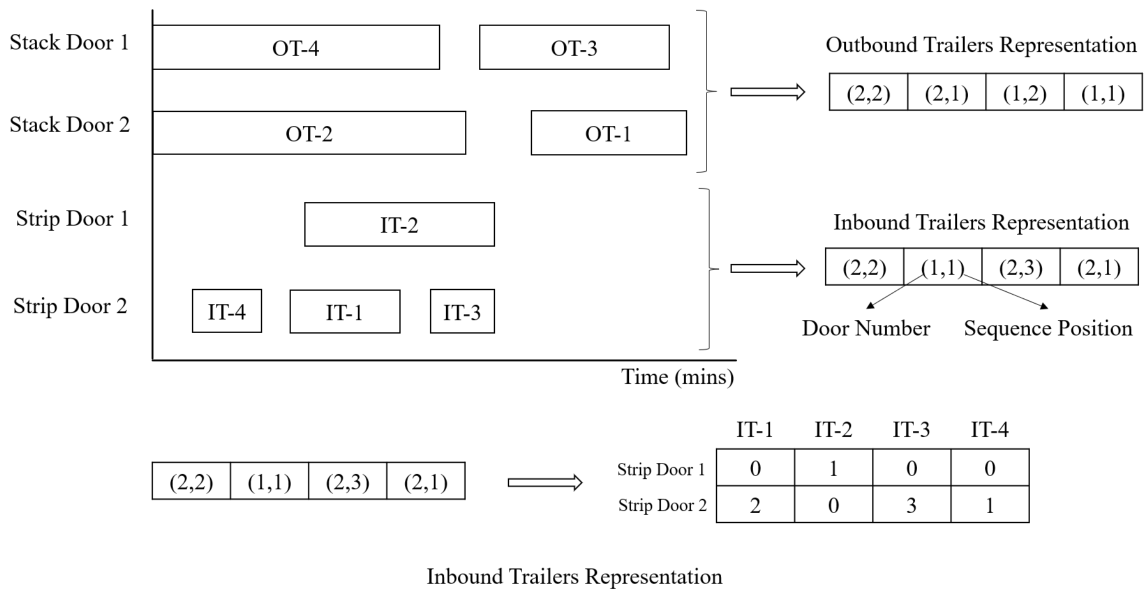


Figure 4.4: Trailer-to-door assignment and sequence representation

The solution representation developed for this study is shown in Figure 4.4. We use one list of tuples for inbound and outbound trailers to represent: (1) trailer-to-door assignment, and (2) position in sequence at assigned door. The index of the list represents the trailer number, the first element of tuple represents assigned door, and the second element of tuple represents the position in sequence of trailer at the assigned door.

To create neighborhood solutions from previous iteration's best solution, pairwise swap or insert operations are applied to either both of inbound and outbound trailer solution or only one of the solutions.

There are two possibilities for the swap operation as shown in Figure 4.5: (1) swap two trailers at different door, and (2) swap two trailers at same gate. The type of swap operation to be applied is randomly selected.

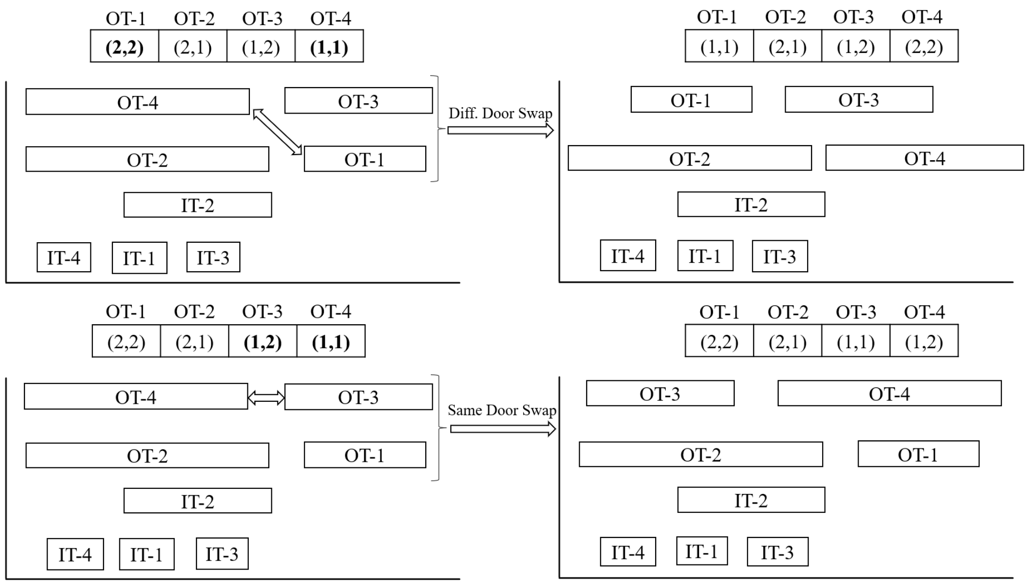


Figure 4.5: Two possibilities for pairwise swap operations shown for outbound trailers at a cross dock with two stack doors.

Insert operation as the name implies inserts a trailer in a different door's trailer sequence as shown in Figure 4.6. Same door insertion is not applied as it is equivalent to same door pairwise swaps. The available positions for insertion in a sequence are calculated and randomly chosen.

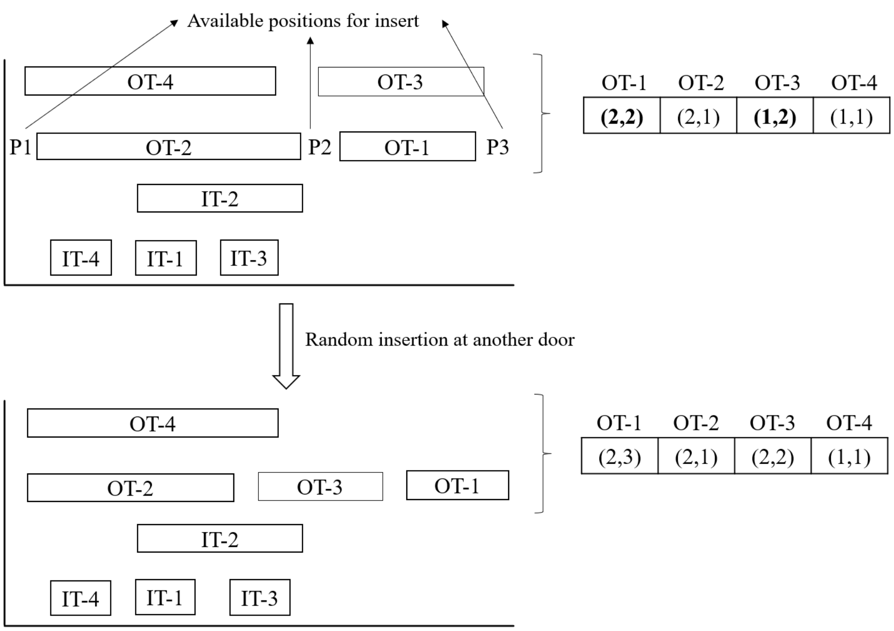


Figure 4.6: Insert operation on outbound trailers at a cross-dock with two stack doors.

Since, the neighborhood solutions have different trailer sequence, the product transfers created using the MDCDH may not lead to a solution closer to global optima. Therefore, the product transfers need to be reconstructed. The inbound trailers arrive at the assigned strip door and leave after unloading all products. Thus the entry and leave time of each trailer can be calculated, but leave time for outbound trailers depends on product transfers or selection of its AIT. We apply a modified MDCDH approach to solve this problem.

In contrast to the original MDCDH we do not create AIT for all the outbound trailers, but instead create subset of outbound trailers at different stack doors by their position in sequence. For example, before swaps hypothetical schedule in Figure 4.5, would have two subsets: Position-1:{OT-4, OT-2} and Position-2:{OT-3, OT-1}. Now the MDCDH is applied first to all outbound trailers at position-1 until all the outbound trailers are scheduled. Then process is repeated until all the outbound trailer subsets have been scheduled. This policy avoids the problem when considering all unscheduled outbound trailers at once for scheduling. Assume for example in Figure 4.5, if OT-3 is selected before OT-4, then it leads to an infeasible solution as OT-4 must be loaded before OT-3. In the next section 4.4 we present comparison of computation time and solution quality for the developed PBSA approach and the exact approach using commercial solver.
The pseudo-code for swap, insert and the PBSA Algorithm is presented in Appendix B.

4.4 Results and Discussion

All the mathematical models and algorithms are coded using Julia v1.4.2 programming language. Gurobi v9.0.0 commercial solver is used to solve the exact optimization problem. All experiments are performed on Clemson University's Palmetto Cluster with the following hardware specifications: Intel Xeon processor, 16 cores and 125GB RAM.

We assume an I-shape for the cross-dock for all the conducted experiments to calculate the transshipment distance. Therefore, number of strip doors and number of stack doors are assumed to be equal i.e. $|I| = |O|$. The transshipment time generation is based on the distance matrix generation developed by Guignard et al. [43]. It assumes the distance between opposite doors is 90 ft and the offset between two consecutive doors is 12 ft. and is given by the equation below:

$$T_{kg} = \begin{cases} 90/\text{forklift speed}, & k = g \\ (90 + 12 * |g - k|)/\text{forklift speed}, & \text{otherwise} \end{cases} \tag{4.32}$$

The supply (product loaded) and demand (product needed) are randomly generated using a custom developed function. The function first generates supply by ensuring each product and inbound trailer has some demand, and then generates demand while ensuring that each outbound trailer and product has a demand, and product demand is equal to the generated supply. Other parameter values or ranges used for the following experiments are given by Table 4.5:

Table 4.5: Input parameter values or range

Parameter	Value/Range
Arrivals (min)	Unif(0, 12*60)
Deadlines (min)	Unif(24*60, 48*60)
Planning Horizon (min)	[0, 48*60]
Load/Unload Time (min)	Unif(2, 5)
Forklift speed (ft/s)	6
Trailer changeover time (min)	75
Penalty ($/min)	Unif(2, 5)
ϕ_1, ϕ_2 (min)	120, 240
λ_1, λ_2, λ_3	1, 2, 4

4.4.1 Computational Results

We developed four hypothetical sets to benchmark the PBSA approach against the exact approach using commercial solver. The four sets represent: small, medium-small, medium-large, and large instances respectively. For commercial solver a time limit of 24h is used. We use RPD to measure solution quality and is calculated using equation 4.31. Ten replications are performed for each instance and average values for RPD and CPU time are reported.

The hyper parameters used for the PBSA is reported in Table 4.6, which are based on the best reported values from Assadi et al. [14]. The hyper parameter values were adjusted for desirable solution quality and CPU time. For readers interested in optimization of the hyper parameter values of meta-heuristics can refer to Assadi et al. [14], Vahdani et al. [77], or Keshtzari et al. [47].

Table 4.6: Hyper-parameter values for the PBSA meta-heruistic

Problem size	Population size	Max iterations	Initial Temperature	Cooling Rate
Small	10	50	50	0.95
Medium-small	20	100	100	0.95
Medium-large	20	250	500	0.92
Large	20	300	600	0.90

Table 4.7 presents the results for average RPD and solution (CPU) time for gurobi solver, MDCDH and PBSA. Gurobi finds the optimal solution for all the small and medium-small instances, and only a feasible solution for all the medium-large and large instances. For medium-large instances, gurobi finds the best solution for all instances but solution time is 24h for all the instances. For large instances, gurobi does not find the best solution in 3 out of 4 instances and solution time is 24h for all instances. This clearly shows the deteriorating performance of gurobi in terms of solution quality and solution time as the problem size increases.

Table 4.7: Average CPU Time and Average RPD Comparison

Problem size	Instance no.	No of doors	No of OT	No of IT	Type of Products	Gurobi		MDCDH		PBSA	
		$\lvert I\rvert = \lvert O\rvert$	$\lvert T_O\rvert$	$\lvert T_I\rvert$	$\lvert P\rvert$	RPD	Time (s)	RPD	Time (s)	RPD	Time (s)
Small	1	1	2	2	1	0	15.78	16.98	7.98	0	3.5
	2	1	2	3	2	0	15.72	33.43	7.38	0.08	3.19
	3	2	3	2	1	0	15.80	10.88	7.53	0.39	3.32
	4	2	3	3	2	0	15.78	10.69	7.31	0.84	3.26
Medium-small	5	4	6	6	5	0	68.67	13.35	8.07	1.52	6.26
	6	4	6	8	6	0	54.49	24.48	8.15	2.10	7.67
	7	6	8	6	5	0	727.05	5.79	8.25	1.75	8.06
	8	6	8	8	6	0	8886.93	8.59	8.25	2.02	9.89
Medium-large	9	10	18	18	8	0	86400	19.16	8.84	2.30	179.40
	10	10	18	20	10	0	86400	32.92	8.98	3.31	242.20
	11	12	20	18	8	0	86400	23.11	9.06	2.61	207.60
	12	12	20	20	10	0	86400	30.56	9.10	3.27	306
Large	13	18	40	35	8	0.6	86400	27.86	19.75	1.67	1053.60
	14	18	35	40	10	2.03	86400	36.80	22.47	2.06	1626
	15	20	40	35	8	0	86400	25.38	22.59	2.79	1294.20
	16	20	40	40	10	1.35	86400	30.20	28.08	1.04	1921.20

MDCDH provides a good starting solution for our PBSA meta-heuristic. The average RPD value for small and medium-small instances is 15.52%. As the instance size increases the average RPD value for medium-large and large instances increases to 28.25%. The solution time for MDCDH is the least for instances 8-16 which includes all the medium-large and large instances. The number of iterations for the MDCDH is equal to the number of outbound trailers and each iteration's solution time is dependent on number of unscheduled outbound trailers, inbound trailers and number of products. The constructive nature of the MDCDH makes it a very fast algorithm to deliver good starting solutions for the PBSA meta-heuristic.

For the PBSA meta-heuristic average RPD for different instance groups is: (1) small: 0.32%, (2) medium-small: 1.85%, (3) medium-large: 2.87%, and (4) large: 1.89%. The worst RPD is 3.31% for instance 10, and best RPD is 0% for instance 1. The PBSA solution time is the best for instances 1-7 and the worst time is 32 mins for the largest instance (instance 16). This shows that PBSA provides near optimal solutions for all the instances under very realistic solution time.

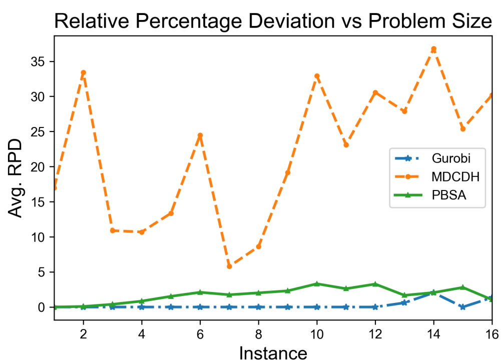


Figure 4.7: Average RPD comparison for solution methodologies

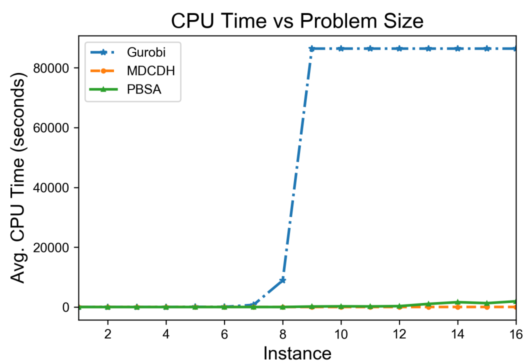


Figure 4.8: Average CPU time for solution methodologies)

The solution quality and solution time for gurobi and PBSA as measured by average RPD values and average CPU time is shown in Figure 4.7 and Figure 4.8 respectively. The PBSA provides very high-quality near optimal solutions for small instances (0.32% avg RPD), and solutions at average RPD of 2.2% for medium-small, medium-large and large instances. The solution time for gurobi is competitive with PBSA for instances 1-7. Instances 8-16 more accurately represent the real world scenarios for multi-door cross-docks. The average solution time for these instances using gurobi increases rapidly to 21.6h and average RPD is 0.44%. Whereas, for PBSA the solution time for such instances is an average of 12.66 mins and average RPD is 2.34%. Therefore, it validates the use of our developed PBSA approach for fast and near-optimal solutions.

4.4.2 Impact of Trailer-to-Door Ratio on Cross-dock Performance

The following set of experiments are performed on a cross-dock with five strip doors, five stack doors, and four product types. We first study the impact of increasing number of inbound trailers and then the impact of increasing number of inbound and outbound trailers on cross-dock performance measures. The experiments aim to find if there exists a recommended value or range of Trailer-to-Door (T/D) ratio for efficient operations at a cross-dock. This knowledge can assist decision makers in selecting the size (number of strip and stack doors) of a cross-dock during the designing phase by using the forecast of number of inbound and outbound trailers to be scheduled.

We perform two sets of experiments to observe the impact of increasing inbound trailer-to-door ratio and increasing both inbound and outbound trailer-to-door ratio on cross-dock performance. For each experiment, each instance is replicated five times and polynomial regression fit is shown for the observed data set. The performance measures used are: (1) make-span, (2) job synchronization error, (3) job delay, (4) job storage time, and (5) inbound trailer wait time.

A job represents transfer of a group of products between an inbound and a outbound trailer. In ideal conditions we want a job to arrive at the cross-dock, unloaded, transferred to assigned stack door and loaded on designated outbound trailer without idle time. If a job arrives earlier at the designated stack door storage is accumulated, leading to congestion at cross-dock terminal. Otherwise if a job arrives later than the docking time of the designated outbound trailer, the outbound trailer has to wait at the strip door. Both these scenarios might be undesirable for a cross-dock operator. Equations used to calculate these measures are presented below, given 'N' number of jobs {1,2,...n}:

For an instance, given a job 'q' between inbound trailer 'i' docked at strip door 'k' and outbound trailer 'j' docked at stack door 'g':

$$\text{OT Arrival Time}_q = e^O_{jg} \tag{4.33}$$

$$\text{Job Arrival Time}_q = e^I_{ik} + \frac{\sum_{p \in P} S_{ip} W_p}{2} + T_{kg} \tag{4.34}$$

$$\text{Average Job Delay} = \frac{\sum_{q=1}^{n} max(0, \text{OT Arrival Time}_q - \text{Job Arrival Time}_q)}{\text{N}} \tag{4.35}$$

$$\text{Average Job Storage Time} = \frac{\sum_{q=1}^{n} max(0, \text{Job Arrival Time}_q - \text{OT Arrival Time}_q)}{\text{N}} \tag{4.36}$$

$$\text{Average Job Synchronization Error} = \frac{\sum_{q=1}^{n} (|\text{OT Arrival Time}_q - \text{Job Arrival Time}_q|)}{\text{N}} \tag{4.37}$$

$$\text{Average IT Wait Time} = e^{I}_{ik} - A_i \tag{4.38}$$

4.4.2.1 Inbound Trailer-to-Door Ratio

In this experiment given a fixed outbound trailer-to-door ratio, we observe the impact of increasing inbound trailer-to-door ratio on the cross-dock performance. These results directly translate to threshold or range of number of inbound trailers a decision maker should schedule in a single planning horizon to obtain desired performance measures. The instance parameters used and observed performance measures for the experiment are given in Table 4.8. The table shows average values of five replications for all the performance measures, and polynomial regression fit is shown in Figure 4.9.

Table 4.8: Inbound T/D Ratio: Instance description and observed performance measures*

Instance	$\|I\|$	$\|O\|$	$\|T_I\|$	$\|T_O\|$	TDR (Inb.)	TDR (Out.)	M.S.	A.J.S.E.	A.J.D.	A.J.S.T.	A.I.T.W.T.
1	5	5	5	10	1	2	601.8	79.02	6.48	72.51	28.32
2	5	5	10	10	2	2	712.5	91.20	21.50	69.70	49.84
3	5	5	15	10	3	2	751.7	70.73	28.21	42.52	52.74
4	5	5	20	10	4	2	778.5	87.59	51.63	35.95	54.43
5	5	5	25	10	5	2	818.3	96.97	64.38	32.59	71.88
6	5	5	30	10	6	2	872.9	105.14	78.35	26.78	101.27
7	5	5	35	10	7	2	982.8	106.19	76.82	28.77	156.34
8	5	5	40	10	8	2	1159.8	144.86	118.60	26.25	232.64
9	5	5	45	10	9	2	1258.8	148.88	120.93	27.95	281.53

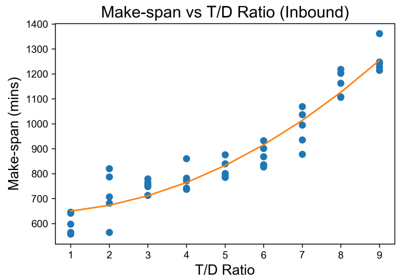
* TDR: Trailer-to-door Ratio, M.S.: Make-span (mins), A.J.S.E.: Avg. Job Synchronization Error (mins), A.J.D.: Avg. Job Delay (mins), A.J.S.T.: Avg. Job Storage Time (mins), A.I.T.W.T.: Avg. I.T. Wait Time (mins)

Make-span of the cross-dock increases with a non-linear trend as we increase the inbound trailer-to-door ratio as shown in Figure 4.9a. In the case of all inbound trailer arrivals at start of planning horizon, we expect the make-span to increase linearly between instance sizes as immediately after an inbound trailer leaves the strip door another unscheduled trailer can replace it. Whereas for scattered arrivals, particularly as the inbound trailer-to-door ratio exceeds 5.0, we see higher increases in make-span between successive instances. For instances 1-5 the average percentage increase in make-span between instances is 8.14%, whereas for instances 5-9 it is observed to to be 11.45%.

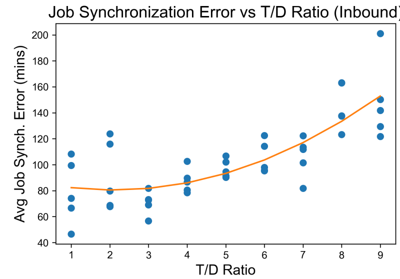
The non-linear increase in make-span can be explained by job synchronization error trend as shown in Figure 4.9b. We observe that job synchronization error particularly increases by 6.87% on average between instances 1-5, and increases by 12.15% on average between instances 5-9. The job synchronization error is absolute value sum of job delay and job storage time. We observe that job delays increase linearly between all the instances but job storage decreases for instances 1-7 and then increases for instances 8-9 as shown in Figure 4.9c.

As inbound trailer-to-door ratio increases given a fixed number of outbound trailers and number of inbound trailers more than outbound trailers, outbound trailers' associated inbound trailers increase and depending on the arrival time may have to wait for inbound trailer. This further leads to an increase in the job delays by an average of 62 mins. between instances as both of these factors contribute to an outbound trailers' waiting time at the stack-door.

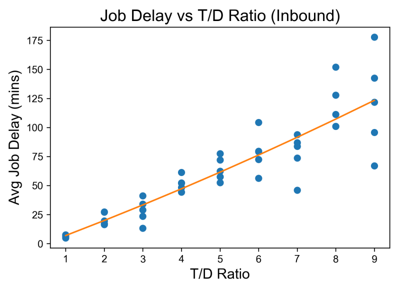
Job storage time measure helps decision makers identify the operational capacity at which storage of jobs is under a desirable limit. Excessive storage can hinder the freight transshipment due to floor congestion. Job storage time shows a non-linear decreasing relationship with inbound-trailer-to-door ratio as shown in Figure 4.9d. We observe a decrease of 16.93% on average between instances 1-5 and decrease of 3% for instances 5-9. For lower inbound trailer-to-door ratios there are lesser associated inbound trailers subsets possible for an outbound trailer during a particular time in planning horizon due to arrival time constraints and products availability. This leads to an outbound trailer waiting for all the associated inbound trailers to arrive at a strip door before outbound trailer's docking at a stack door. As the number of inbound trailers increase the product availability during a point of time in planning horizon increases and thus outbound trailers' wait time to dock at a stack door also decreases. This leads to a decrease in job storage time.



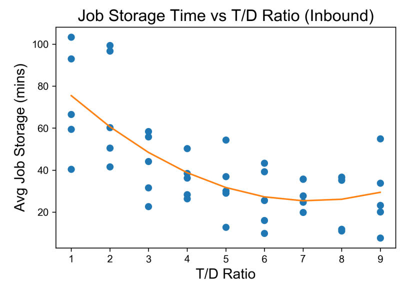
(a) Impact of inbound T/D ratio on cross-dock make-span



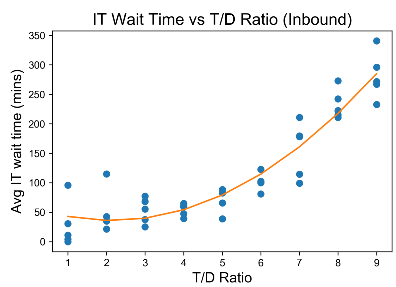
(b) Impact of inbound T/D ratio on job synchronization error



(c) Impact of inbound T/D ratio on job delays



(d) Impact of inbound T/D ratio on job storage time



(e) Impact of inbound T/D ratio on inbound trailer wait-time

Figure 4.9: Impact of inbound trailer-to-door ratio on cross-dock performance

IT wait time measure is very useful from the perspective of inbound carrier. Excessive wait time for inbound carriers at a cross-dock after arrival decreases the utilization of inbound trailers for future pickup jobs. Thus identifying this measure trend against inbound trailer-to-door ratio can help decision makers in planning phase to choose the number of strip doors to be constructed or in operational planning to decide number of inbound trailers to be scheduled in a single planning period.

The IT wait time increases non-linearly with increase in inbound trailer-to-door ratio due to lower availability of strip doors as shown in Figure 4.9e. For instances 1-5 average wait time for an inbound trailer is relatively lower at an average of 51 mins, whereas for instances 5-9 the average inbound trailer wait time increases approximately four times to 193 mins. The average percentage increase in wait time between successive instances is 29% for instances 1-5 and 41% for instances 5-9.

The key insights from these experiments, for scenarios where number of inbound trailers are more than number of outbound trailers, are: (1) Make-span increases non-linearly with increase in inbound trailer-to-door ratio, ratios higher than 5.0 may be undesirable for cross-dock operators, (2) Job storage time decreases with increasing inbound trailer-to-door ratio non-linearly, and relatively higher and may be undesirable for ratios 1-4, and (3) Inbound trailer wait-time increases non-linearly with increasing inbound trailer-to-door ratio and may be undesirable for inbound trailer-to-door ratios higher than 5.0.

4.4.2.2 Inbound and Outbound Trailer-to-Door Ratio

These experiments observe the impact of inbound and outbound trailer-to-door ratio on the performance measures. These results helps the decision makers identify number of inbound and outbound trailers that can be scheduled in a planning horizon to achieve desired performance measures. The instance parameters used and observed values for the performance measures are given in Table 4.9. The performance measure values in the table represent the average values of five replications of an instance.

The make-span of the cross-dock increases non-linearly as both number of inbound and outbound trailers increase as shown in Figure 4.11a. The trend shows that for instances 1-5 make-span increases by 6% on average between successive instances and by approx. 12% between instances 5-9.

Table 4.9: Inb. & Out. T/D Ratio: Instance description and observed performance measures*

Instance	$\|I\|$	$\|O\|$	$\|T_I\|$	$\|T_O\|$	TDR (Inb.)	TDR (Out.)	M.S.	A.J.S.E.	A.J.D.	A.J.S.T.	A.I.T.W.T.
1	5	5	5	5	1	1	669	125.45	19.38	105.26	2.36
2	5	5	10	10	2	2	713.6	91.49	20.14	91.49	40.90
3	5	5	15	15	3	3	762.3	76.40	20.30	76.40	38.90
4	5	5	20	20	4	4	779.4	53.35	18.36	53.35	52.49
5	5	5	25	25	5	5	836.2	58.86	16.77	58.86	75.64
6	5	5	30	30	6	6	923.4	61.34	14.66	61.34	124.69
7	5	5	35	35	7	7	1062	55.23	12.25	55.23	168.62
8	5	5	40	40	8	8	1159.9	67.16	10.32	67.16	237.03
9	5	5	45	45	9	9	1308.4	64.31	10.94	64.31	283.71

* TDR: Trailer-to-door Ratio, M.S.: Make-span (mins), A.J.S.E.: Avg. Job Synchronization Error (mins), A.J.D.: Avg. Job Delay (mins), A.J.S.T.: Avg. Job Storage Time (mins), A.I.T.W.T.: Avg. I.T. Wait Time (mins)

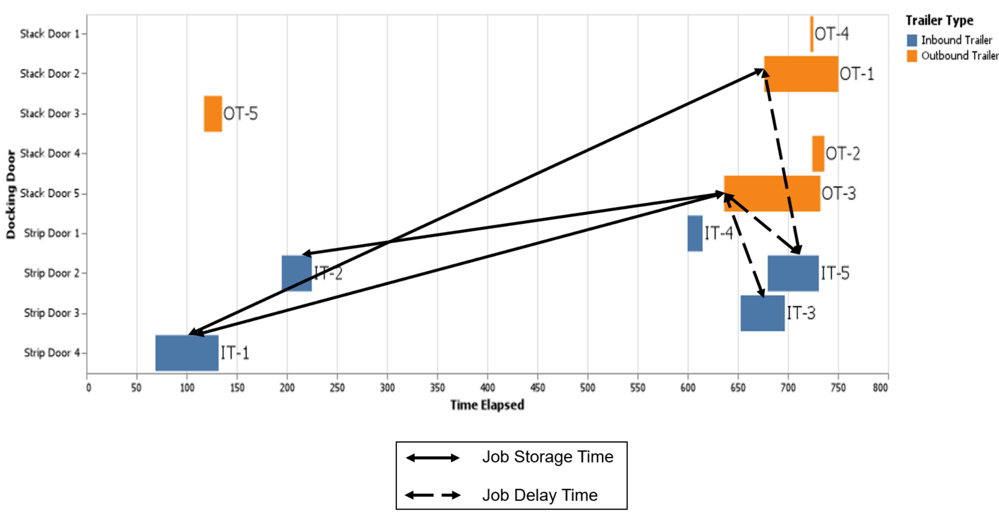


Figure 4.10: Gantt chart for a replication of Instance 1 (only utilized docking doors shown).

The job synchronization errors are higher for instances with lower inbound and outbound trailer-to-door ratios and the trend is shown in Figure 4.11b. For instances 1-4 job synch. error decreases by an average of 24.5% between successive instances and increases by an average of 4.5% for instances 4-9. For lower ratios the scheduling is very dependent on arrivals of inbound trailers. Highly scattered arrivals lead to higher synchronization errors, particularly higher job storage time as outbound trailers are scheduled just-in-time to reduce stack door idling time. As shown in

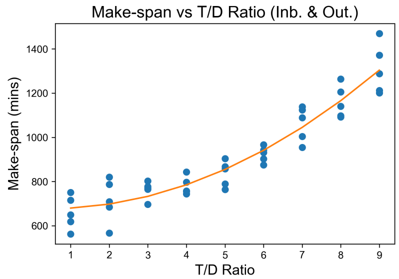
Figure 4.10 OT-1 needs jobs from IT-1, and IT-5 to complete its loading. Instead of the scenario, loading products from IT-1 and waiting for IT-5, OT-1 delays its docking to arrive just-in-time and leave stack door at the same time as it would have in the former scenario. For higher ratios, the synchronization error starts to increase due to increasing impact of job storage time, and is explained in the following discussion.

The job delays are relatively less as compared to storage, and decrease non-linearly with increase in inbound and outbound trailer-to-door ratios as shown in Figure 4.11c. For instances 1-5 job delays decrease by an average of 3.4% between successive instances and by an average of 9.69% for instances 5-9. As the number of inbound and outbound trailers, product interchangeability ensures more product availability across the planning horizon. Therefore, lesser job delays are observed for instances with higher inbound and outbound trailer ratios.

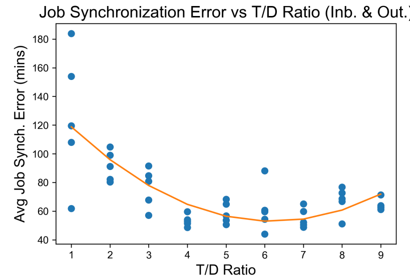
Job storage time as explained above is higher for lower inbound and outbound trailer-to-door ratios as shown in Figure 4.11d. As the ratios increase first we observe a decrease in storage time and then followed by an increase in storage time. For instances 1-4 the job storage time decrease by an average of 30% between successive instances and increases by approx. 10% for instances 4-9.

In contrast to previous experiments we observe an increase in job storage for instances 4-9. The reason for this trend reversal is increase in number of outbound trailers to be scheduled. The increase in outbound trailer-to-door ratio creates a bottleneck for outbound trailers to arrive at the strip door and load the needed products. When number of inbound trailers are significantly more than outbound trailers (instances 6-9), most outbound trailers are already docked at strip door and as soon as the required products arrive, with no or very little storage time are loaded.

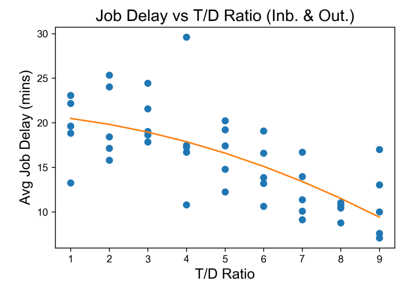
The inbound trailer wait time is found to increase non-linearly with increase in inbound and outbound trailer-to-door ratios as shown in Figure 4.11e. The average wait time for an inbound trailer is 42 mins. for instances 1-6 and 204 mins. for instances 7-9. Therefore, from inbound carrier's perspective ratios higher than 5 or 6 might be undesirable.



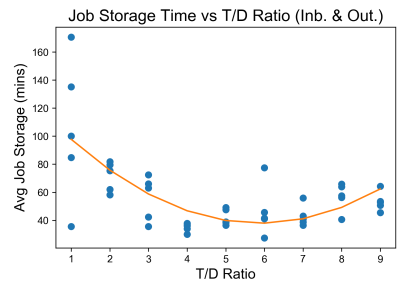
(a) Impact of inbound and outbound T/D ratio on cross-dock make-span



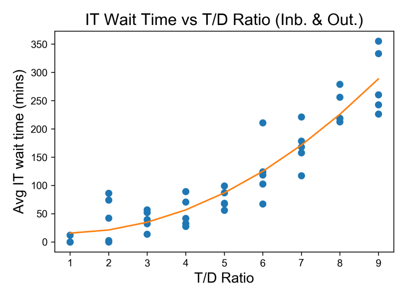
(b) Impact of inbound and outbound T/D ratio on job synchronization error



(c) Impact of inbound and outbound T/D ratio on job delays



(d) Impact of inbound and outbound T/D ratio on job storage time



(e) Impact of inbound and outbound T/D ratio on inbound trailer wait-time

Figure 4.11: Impact of inbound and outbound trailer-to-door ratio on cross-dock performance

The key insights from this experiment are: (1) Make-span increase non-linearly with increase in inbound and outbound trailer-to-door ratios and ratios higher than 5.0 might be undesirable for cross-dock operators, (2) Job storage time first decreases and then increases with increase in inbound and outbound trailer-to-door ratios, and thus ratios between 4.0-7.0 would lead to lower storage time at cross-dock, and (3) Inbound trailer wait time increases non-linearly with inbound and outbound trailer-to-door ratios, ratios higher than 6.0 might be undesirable for an inbound carrier.

4.4.2.3 Impact of Inter-arrival Time on Cross-dock Performance

The asynchronous arrivals of inbound trailers impact the cross-docking process due to the interdependence of inbound and outbound scheduling processes. The late arrival of an outbound trailer's AIT would result in an outbound trailer spending more time at the cross-dock to complete its required loading. This further may result in extending the make-span of the cross-dock. It is interesting to study the impact of arrival times of inbound trailers on the performance measures like make-span, job storage time and inbound trailer wait-time. The results will provide cross-dock operators and freight carriers with useful insights on what storage levels to expect or what inbound trailers wait-times to expect under a given cross-dock configuration and inter-arrival time data distribution.

We assume an exponential distribution for the inter-arrival time random variable. The cross-dock is assumed to have three stack and strip doors each, and the scheduling is performed for 10 inbound trailers, 8 outbound trailers given two product types. Five replications are performed for each inter-arrival time instance. The first arrival is randomly selected between [0 mins, 60 mins]. The successive arrival times are calculated as the sum of arrival time of previous inbound trailer and an inter-arrival time randomly sampled from an exponential distribution with mean values given in Table 4.10. The instance parameters used and observed values for the performance measures are given in Table 4.10. The performance measure values in the table represent the average values of five replications of an instance.

The increase in mean inter-arrival time impacts the cross-dock make-span non-linearly as shown in Figure 4.12a. The average increase in make-span when mean inter-arrival time increases from 10 mins to 20 mins and 20 mins to 30 mins is 8.47%. Whereas the average increase between successive instances for instances 5-8 is 16.20%. Therefore, higher mean inter-arrival times can lead to non-linear increase in make-span. This trend can be explained by the increase in job storage time with increase in mean inter-arrival time and is explained next.

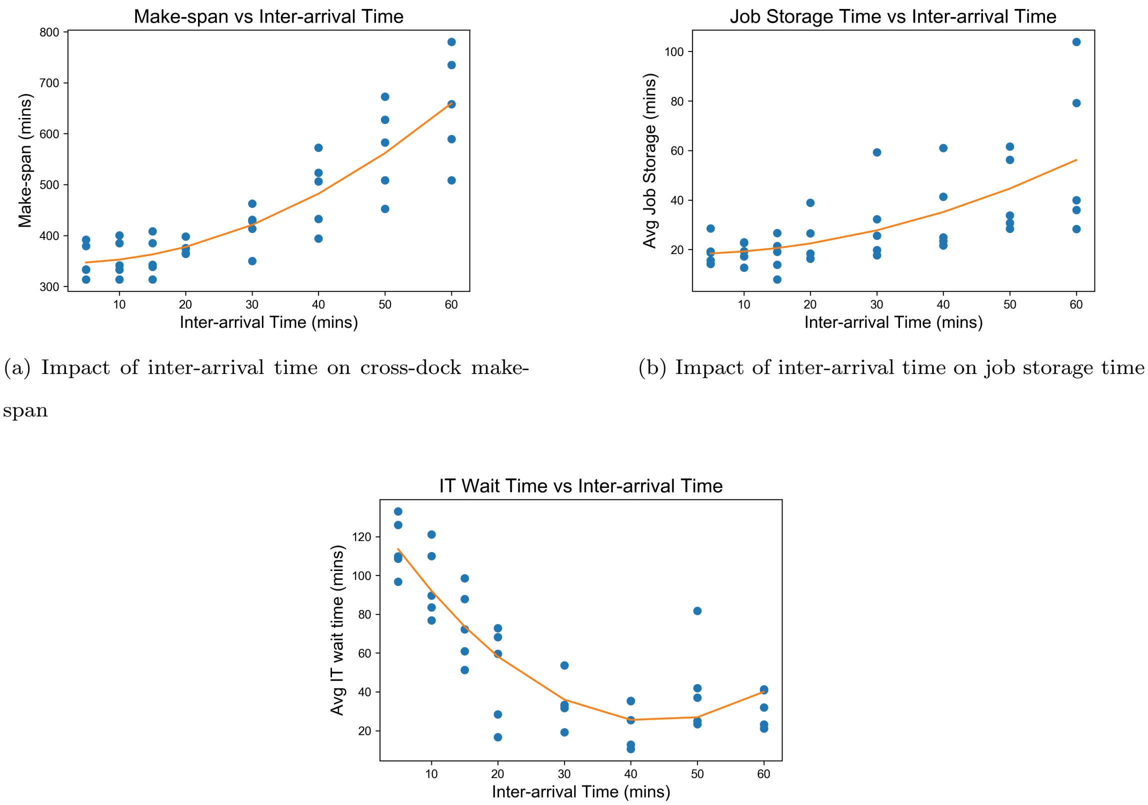
Table 4.10: Inter-arrival Time: Instances & observed performance measures*

Instance	$\lvert I \rvert$	$\lvert O \rvert$	$\lvert T_I \rvert$	$\lvert T_O \rvert$	I.T.	M.S.	A.J.S.T.	A.I.T.W.T.
1	3	3	10	8	5	350.16	19.27	114.84
2	3	3	10	8	10	354.57	18.99	96.28
3	3	3	10	8	15	357.58	17.80	74.20
4	3	3	10	8	20	375.36	23.28	49.14
5	3	3	10	8	30	416.97	30.96	34.12
6	3	3	10	8	40	485.77	34.47	23.92
7	3	3	10	8	50	568.77	42.14	41.80
8	3	3	10	8	60	654.26	57.46	31.68

* I.T.: Inter-arrival Time (mins), M.S.: Make-span (mins), A.J.S.T.: Avg. Job Storage Time (mins), A.I.T.W.T.: Avg. I.T. Wait Time (mins)

The job storage time increases with increase in mean inter-arrival time. Higher mean inter-arrival time leads to more scattered arrivals of inbound trailers. Keeping in mind the just-in-time approach for outbound trailer docking, an outbound trailer waits for the last arriving inbound trailer belonging to its AIT and docks at the stack door just-in-time to leave at the earliest time possible. During this just-in-time process other earlier arrived inbound trailers belonging to outbound trailer's AIT must unload the jobs and store it at the outbound trailer's designated stack door. The job storage time increases as the inter-arrival times for the inbound trailers in the AIT increases. The job storage time on average for instances 1-3 is approx. 19 mins and for instances 4-9 is approx. 38 mins.

From the inbound carrier's perspective we observe the inbound trailer wait-time decreases non-linearly with increase in mean inter-arrival time. The decreasing trend is justified by the increasing spread of inbound trailers' arrival times. As for an incoming inbound trailer, cross-dock has more time to unload the previously arrived inbound trailers and get the strip door ready for next docking. We observe the wait time for an inbound trailer for instances 1-4 is approx. 84 mins on average and for instances 5-8 is approx. 33 mins in average.



(a) Impact of inter-arrival time on cross-dock make-span

(b) Impact of inter-arrival time on job storage time

(c) Impact of inter-arrival time on inbound trailer wait-time

Figure 4.12: Impact of inter-arrival time on cross-dock performance

The key insights from this experiment are: (1) make-span increases non-linearly with increasing mean inter-arrival time, (2) job storage increases with increase in mean inter-arrival time given an exponential distributed, and can help cross-dock operators decide the storage space required, and (3) inbound trailer wait time decreases non-linearly with increase in mean inter-arrival time, and from the inbound carriers' perspective lower mean inter-arrival times might be more desirable for higher trailer turnover rate.

4.5 Conclusion and Future Work

This study addresses the multi-door and multi-product cross-dock scheduling problem, which is significantly less studied problem than the single-door counter-part. This problem includes several features like product interchangeability, asynchronous arrival times for inbound trailers, soft deadlines for outbound trailers and non-linear tardiness penalty for outbound trailers. We developed a mixed integer non-linear programming based model for the described problem and then reformulate it to a mixed integer linear programming model. The problem is well-known to be NP-hard, as well as we aim to use this model for online applications. Therefore, we develop MDCDH based on seminal work by Yu et. al [83, 84], and a population based simulated annealing meta-heuristic to tackle the computational challenges for solving the problem in real-time for large instances.

The experiments show that the proposed hybrid meta-heuristic leads to near-optimal solutions with a maximum RPD of 3.27% and matches the solution quality with exact solutions for very large and realistic instances. The solution time for the meta-heuristic is less than the exact model solved using gurobi commercial solver for all the instances, and significantly for larger instances. We also observe the impact of inbound trailer-to-door ratio and inbound and outbound trailer-to-door ratios on cross-dock performance. We identify key trends in performance measures like make-span, job storage time and inbound trailer wait time that might be used by cross-dock operators and inbound carriers to optimize their processes to desired standards. The impact of inbound trailer-to-door ratio, inbound and outbound trailer-to-door ratios and mean-inter-arrival time on the performance measures is presented.

The study assumes cross-dock shape to be I-shaped, which is most prevalent in real-world applications. It would be interesting to study the impact of cross-dock shapes on the various performance measures like make-span, job storage time, and inbound trailer wait time. This would help during the decision makers for cross-dock design stage, and identify, depending on the forecasted inbound and outbound trailers, the better suited shape and size. We also assume all outbound trailers to be present at cross-dock at start of planning horizon and soft deadlines on outbound trailers. Another scenario could be asynchronous outbound trailer arrivals and hard deadlines for outbound trailers. In such a case the outbound trailer's remaining products could be loaded on other outbound trailer destined to the same end-customer.

In future research we aim to apply the developed model and solution methodology to an online problem with uncertain arrival times of inbound trailers. The inbound trailers could be delayed due to a breakdown or traffic conditions or arriving earlier. In such a case we could use information exchange between cross-docks and inbound carriers to update inbound trailer arrival times to cross-dock and to update cross-dock schedule to inbound carriers. Each time there is an update in arrival time of an inbound trailer, carrier informs cross-dock and cross-dock in turn re-optimizes the remaining schedule and informs inbound carriers about updated schedule. This would help us in closing on the research gap of developing synchronized cross-dock scheduling problem and optimize both cross-dock and inbound carrier's processes. The developed solution methodology is suitable for such an application as re-optimization must be done in real-time to inform inbound carriers in a timely manner.

We address the multi-door cross-dock scheduling problem collectively for inbound and outbound trailers for asynchronous inbound trailer arrivals. The study also develops a meta-heuristic solution algorithm to solve the problem in real-time for large instances. This research will help to close the research gaps in cross-dock scheduling problems and assist the decision makers to tackle the real-world problems.

Appendices

Appendix A Appendix to Chapter 3

L-shaped Method Algorithm: This algorithm is developed based on the L-shaped method developed by Slyke et al. [79].

Algorithm 1: L-shaped Method

iter $\leftarrow$ 0, UB$^{\text{iter}}$ $\leftarrow$ + ∞, LB$^{\text{iter}}$ $\leftarrow$ - ∞;
convergence $\leftarrow$ False;
while *convergence == False* **do**
    iter $\leftarrow$ (iter+1);
    Solve **[LD-MP]** for $\vec{\xi}^{\text{iter}}$,$\vec{\theta}^{iter}$ and Obj_val;
    if *Obj_val* $>LB^{iter}$ **then**
        LB$^{\text{iter}}$ $\leftarrow$ Obj_val;
    end
    $\vec{\hat{\xi}}^{\text{iter}} \leftarrow \vec{\xi}^{\text{iter}}$, $\vec{\hat{\theta}}^{iter} \leftarrow \vec{\theta}^{iter}$;
    temp_UB $\leftarrow$ $\vec{F}.\vec{\xi}^{\text{iter}}$;
    for $\omega \leftarrow \omega_1$ **to** ω_{n_scen} **do**
        Solve **[DSP]** for $Q_\omega(\vec{\hat{\xi}}^{\text{iter}})$ and $\vec{\pi}_\omega^{\text{iter}}$;
        temp_UB$\leftarrow$ (temp_UB+$p(\omega).Q_\omega(\vec{\hat{\xi}}^{\text{iter}})$);
    end
    if *temp_UB* $<UB^{iter}$ **then**
        UB$^{\text{iter}}$ $\leftarrow$ temp_UB
    end
    if $\left(\frac{UB^{iter}-LB^{iter}}{UB^{iter}}\right) \leq \epsilon$ **then**
        convergence $\leftarrow$ True;
    else
        n_cuts $\leftarrow$ 0;
        for $\omega \leftarrow \omega_1$ **to** ω_{n_scen} **do**
            if $\hat{\theta}_\omega^{iter} < Q_\omega(\vec{\hat{\xi}}^{iter})$ **then**
                $V_\omega^{\text{iter}} \leftarrow (V_\omega^{\text{iter-1}} \cup \vec{\pi}_\omega^{\text{iter}})$;
                n_cuts $\leftarrow$ n_cuts + 1;
            end
        end
        if *n_cuts == 0* **then**
            convergence $\leftarrow$ True;
        end
    end
end

Level Decomposition Algorithm: This algorithm is developed based on the level decomposition developed by Lemarechal et al. [50].

Algorithm 2: Level Decomposition

iter $\leftarrow 0$, $F_{up}^{\text{iter}} \leftarrow +\infty$, $F_{low}^{\text{iter}} \leftarrow -\infty$, $\lambda \in [0,1], \vec{\xi}^*_{iter} \leftarrow$ zeros(13) ;
convergence $\leftarrow$ False;
while *convergence == False* **do**
    iter $\leftarrow$ (iter+1);
    $F_{lev}^{iter} = F_{low}^{iter} + \lambda(F_{up}^{iter} - F_{low}^{iter})$;
    Solve **[LD-MP]** for $\vec{\xi}^{\text{iter}}, \vec{\theta}^{iter}$ and Obj_val;
    while *termination_status([**LD-MP**]) != Optimal* **do**
        $F_{low}^{iter} \leftarrow F_{lev}^{iter}$;
        $F_{lev}^{iter} = F_{low}^{iter} + \lambda(F_{up}^{iter} - F_{low}^{iter})$;
        Solve **[LD-MP]** for $\vec{\xi}^{\text{iter}}, \vec{\theta}^{iter}$ and Obj_val;
    end
    $\hat{\vec{\xi}}^{\text{iter}} \leftarrow \vec{\xi}^{\text{iter}}$, $\hat{\vec{\theta}}^{iter} \leftarrow \vec{\theta}^{iter}$, $\vec{\xi}^*_{iter+1} \leftarrow \vec{\xi}^{iter}$;
    temp_F$_{up} \leftarrow \vec{F}.\vec{\xi}^{\text{iter}}$;
    for $\omega \leftarrow \omega_1$ **to** ω_{n_scen} **do**
        Solve **[DSP]** for $Q_\omega(\hat{\vec{\xi}}^{\text{iter}})$ and $\vec{\pi}_\omega^{\text{iter}}$;
        temp_F$_{up} \leftarrow$ (temp_F$_{up} + p(\omega).Q_\omega(\hat{\vec{\xi}}^{\text{iter}})$);
    end
    if *temp_F$_{up}$* $< F_{up}^{iter}$ **then**
        $F_{up}^{\text{iter}} \leftarrow$ temp_F$_{up}$;
    end
    if $\left(\frac{F_{up}^{iter} - F_{low}^{iter}}{F_{up}^{iter}}\right) \leq \epsilon$ **then**
        convergence $\leftarrow$ True;
    else
        n_cuts $\leftarrow$ 0;
        for $\omega \leftarrow \omega_1$ **to** ω_{n_scen} **do**
            if $\hat{\theta}_\omega^{iter} < Q_\omega(\hat{\vec{\xi}}^{iter})$ **then**
                $V_\omega^{\text{iter}} \leftarrow (V_\omega^{\text{iter-1}} \cup \vec{\pi}_\omega^{\text{iter}})$;
                n_cuts $\leftarrow$ n_cuts + 1;
            end
        end
        if *n_cuts == 0* **then**
            convergence $\leftarrow$ True;
        end
    end
end

Appendix B Appendix to Chapter 4

Swap Algorithm: This algorithm is used to swap two trailers of the same type (inbound or outbound).

Algorithm 3: Swap Algorithm

Input: Original Trailer Sequence

Output: New Trailer Sequence

Randomly select two unique trailers to apply swap;

Swap assigned door for selected trailers;

Swap assigned sequence position for selected trailers;

Insert Algorithm: This algorithm is used to remove a trailer from it's assigned door sequence and insert at another door's sequence

Algorithm 4: Insert Algorithm

Input: Original Trailer Sequence

Output: New Trailer Sequence

Randomly select a trailer to apply insert;

Randomly assign a new door different from the original door;

Randomly assign new sequence position at new door;

Update sequence position of all impacted trailers at the original and new door;

Mutli-Criteria Decision Making (MCDM) Algorithm: This algorithm is used to select the best alternative using a weighted criterion given a pair of evaluation criteria.

Algorithm 5: MCDM Algorithm

Input: List_1, List_2, β_1, β_2

Output: Selected_trailer

Best_sol_1 $\leftarrow min(List\_1)$;

Best_sol_2 $\leftarrow min(List\_2)$;

RPD_1 $\leftarrow$ Apply Equation 4.31 to Best_sol_1;

RPD_2 $\leftarrow$ Apply Equation 4.31 to Best_sol_2;

for *Trailer in List_1(or List_2)* **do**

  Weighted_Dev[Trailer] $\leftarrow \beta_1 * RPD\_1[Trailer] + \beta_2 * RPD\_2[Trailer]$;

end

Selected_trailer $\leftarrow$ **argmin**(Weighted_Dev);

Multi-Door Cross-Dock Heuristic (MDCDH) Algorithm:

Algorithm 6: MDCDH Heuristic

Input: Supply, OT_Demand, Arrivals, Deadline, T_O, T_I

Output: Schedule_IT, Schedule_OT

```
Unscheduled_OT ← T_O  Unscheduled_IT ← T_I  Storage ← ϕ;
while Unscheduled_OT is non-empty do
    AIT ← ϕ ;                                          // Begin First-stage
    for OT in Unscheduled_OT do
        OT_Demand ← OT_Demand after using Storage;
        Available_IT ← Unscheduled_IT;
        while OT_Demand Unsatisfied do
            EPA (Earliest Product Availability) ← ϕ;
            EUT (Excess Unloading Time) ← ϕ;
            for IT in Available_IT do
                if IT has Available Supply then
                    Calculate and Update IT EPA;
                    Calculate and Update IT EUT;
                end
            end
            Selected_IT ← MCDM(EPA, EUT);
            AIT[OT] ← Selected_IT;
            OT_Demand ← OT_Demand after using Selected_IT's Supply;
            Available_IT ← Available_IT \ Selected_IT ;    // End First-stage
        end
    end
    TD (Time to Deadline) ← ϕ ;                         // Begin Second-stage
    UT (Unload Time) ← ϕ;
    for OT in Unscheduled_OT do
        Calculate and Update TD with (OT Departure Time - OT Deadline);
        Calculate and Update UT with AIT's Total Unload Time;
    end
    if min(TD) <= 0 then
        Selected_OT ← argmin(TD);
    else
        Selected_OT ← MCDM(TD, UT);
    end
    Schedule Selected_OT and ITs in AIT at Docking Doors;
    Unscheduled_OT ← Unscheduled_OT \ Selected_OT;
    Unscheduled_IT ← Unscheduled_IT \ Selected_IT;
    Update Storage ;                                    // End Second-stage
end
```

Pseudo code for Population Based Simulated Annealing (PBSA) Algorithm:

```
Algorithm 7: PBSA Algorithm:
Input: pop_size, max_iter, init_temp, cool_rate
Output: Sch_IT, Sch_OT
Sch_IT, Sch_OT ← MDCDH(T_I, T_O);
Incumbent_sol ← Obj_val using Sch_IT, Sch_OT;
Seq_IT and Seq_OT ← Generated using Sch_IT, Sch_OT;
temp_curr ← init_temp, current_iter ← 0;
while current_iter <= max_iter do
    current_iter += 1;
    Population ← φ;
    for sol in 1:pop_size do
        New_Seq_IT, New_Seq_OT ← Swap/Insert(Seq_IT, Seq_OT) or Do-nothing;
        Population[sol] ← New_Seq_IT, New_Seq_OT;
    end
    Fitness ← φ;
    Schedule ← φ;
    for sol in 1:pop_size do
        New_Sch_IT ← Created using New_Seq_IT;
        Create T_O^i ⊆ T_O for each position 'i' at stack doors in New_Seq_OT;
        New_Sch_OT ← φ;
        for Each subset T_O^i do
            New_Sch_OT^i ← MDCDH(T_I, T_O^i);
            New_Sch_OT ← New_Sch_OT^i;
        end
        Fitness[sol] ← Obj_val using New_Sch_IT & New_Sch_OT;
        Schedule[sol] ← New_Sch_IT & New_Sch_OT;
    end
    Current_sol = min(Fitness);
    Δ = Current_sol - Incumbent_sol;
    Accept_prob = exp(-Δ / temp_curr);
    if Δ < 0 then
        Incumbent_sol ← Current_sol;
        Seq_IT, Seq_OT ← Population[argmin(Fitness)];
        Sch_IT, Sch_OT ← Schedule[argmin(Fitness)];
    else if Accept_prob >= rand(0,1) then
        Incumbent_sol ← Current_sol;
        Seq_IT, Seq_OT ← Population[argmin(Fitness)];
        Sch_IT, Sch_OT ← Schedule[argmin(Fitness)];
    end
    temp_curr ← cool_rate*temp_curr;
end
```

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