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MODELING THE INTERRELATIONSHIP BETWEEN VESSEL AND TRUCK TRAFFIC AT MARINE CONTAINER TERMINALS

by

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A Dissertation submitted to the

Graduate School-New Brunswick

Rutgers, The State University of New Jersey

in partial fulfillment of the requirements

for the degree of

Doctor of Philosophy

Graduate Program in Civil and Environmental Engineering

written under the direction of

Dr. Maria Boile

and approved by

New Brunswick, New Jersey

[May, 2010]

ABSTRACT OF THE DISSERTATION

MODELING THE INTERRELATIONSHIP BETWEEN VESSEL AND TRUCK

TRAFFIC AT MARINE CONTAINER TERMINALS

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This dissertation established a relation between truck gate activities and wharf operations at a marine container terminal using analytical and simulation approaches. This objective was maintained by observing the marine yard, which acts as a buffer link between the wharf and gates since containers stay in the yard for some period before they are transferred to the gates or the wharf. As a result, the container dwell time (CDT) was a major factor in developing this link. The study identified factors that affect CDT (CDT determinants). The dissertation presented an analytical approach to model CDT based on factors influencing CDT. The study provided comprehensive reviews of data mining procedures to reveal the suitable techniques in estimating CDT based on its determinant factors. Three Data Mining (DM) procedures were employed to estimate and predict the CDT and the results were compared with the observed data to find the robust model in maintaining this objective. The result of the selective model was applied to measure how changes in the CDT determinants could impact the CDT, yard capacity, and terminal revenues.

The dissertation related the gate and the apron activities using the CDT and discerned the patterns for departure and arrival of containers at truck gates an hourly and daily basis. These distributions were employed to develop alternative scenarios estimating truck gate volumes based on the escalated apron's container volume and the CDT changes. Finally, the research validated the outcomes of the analytical and modeling phases on a virtual environment using a simulation technique. The dissertation also proposed an appointment system at truck gates and at the truck interchange to ease the congestion at terminal gates.

The dissertation provides port policy makers with valuable information that can facilitate their future decision making in operational, tactical and strategic levels. The analytical approach of this dissertation is designed to depict the value of information collected by terminal operators on a daily basis. The dissertation utilized this data to develop a model, define patterns, and provide findings which can be utilized in tactical and strategic levels; while the simulation approach proposed operational scenarios to ease the congestion at the terminal gates.

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ACKNOWLEDGEMENT AND DEDICATION

I would like to extend my sincere appreciation to faculty and staff in Center for Advanced Infrastructure and Transportation particularly Dr. Ali Maher, Dr. Patrick Szary, and Azam Kalantari for their supports throughout the completion of this study.

I would like to extend my gratitude to my advisor, Dr. Maria Boilé. I am grateful to the committee members Dr. Mohsen Jafari, Dr. Kaan Ozbay, and Dr. Trefor Williams, for their critical review and constructive suggestions during the course of this work.

Last and certainly not least I would like to express my love to my family; my husband, Hassan, my son, Nima, and my sweet daughter, Sonya who have always been there for me with love, and support. I owe them everything.

This thesis is dedicated to the memory of my parents, Kamal Moini, and Pouran Mosadegh

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List of Abbreviations

3PL	3 rd Party Logistic
AGV	Automated Guided Vehicle
ANN	Artificial Neural Network
ASC	Automated Stacking Crane
BoL	Bill of Lading
CDT	Container Dwell Time
DM	Data Mining
GSC	Global Supply Chain
IFT	Intermodal Freight Transportation
JIT	Just In Time
LR	Logistic Regression
NOA	Notice of Arrival
NB	Naïve Bayesian
NBTree	Hybrid Naïve Bayes and Decision Tree
OBC	Overhead Bridge Crane
RMG	Rail Mounted Gantry
RMSE	Root Mean-Squared Error
RTG	Rubber Tyred Gantry
Та	Truck with the appointment
TE	Transfer Equipment
TEU	Twenty-foot Equivalent Unit
Tr	Truck with the random arrival
TTT	Truck Travel Time

1.1 Problem Definition

Intermodal Freight Transportation (IFT) involves the shipping of cargo loaded into a container from an origin to a destination using various modes of transportation (e.g., truck, rail, water) wherein the container is moved seamlessly between the modes. The rationale behind the IFT is to combine the best feature of each of its composite modes: the flexibility of truck in local pickup and delivery with the low line haul cost of rail and water. The cost of hauling cargo is further reduced by shorter handling time at the transfer facilities with the improved security and reduced delivery time. With this consideration, IFT system becomes the leading freight transportation network in the global trades. The US IFT volume grew more than 400% in 35 years from about 3 million Twenty-foot Equivalent Unit (TEU) in 1970, to more than 12 million TEU in 2005¹.

With more than 95% of the US import and export volumes moving by water¹, marine terminals are essential nodes in the IFT system. Marine terminals represent facilities in which cargo is transferred from a vessel to truck or rail. Different cargos have different characteristics (break bulk, liquid bulk, dry bulk, containerized, etc) and require different handling procedures. For instance, in Ro-Ro terminals, cargo remains on wheels throughout its transfer between the vessel, the terminal gate, and the hinterland. Liquid

¹ MTSNAC Education Team, The Marine transportation system and the supply chain, www.mtsnac.org/docs/powerpnt/2006-08-01. Accessed August 2006.

bulk cargo handling is typically automated, requiring specialized handling equipment and storage facilities.

Containers are loaded or unloaded from a vessel by quay cranes and are handled by specialized equipment for horizontal and vertical transport in the terminal yard, where they are stored temporarily until they are transferred to their next mode of transport. The container body protects the cargo from damage and loss in transloading.

Containerized cargo is the predominant and fastest increasing type of cargo, especially for inter-continental cargo traffic. Currently, 85% of US intermodal cargo volume, including domestic and international, is hauled in containers¹. The increase of global containerized trade which had a volume of 58 Million TEU in 2001 is predicted to reach 129 Million TEU in 2011². The US DOT's Federal Highway Administration predicts that the US will experience an overall doubling of international freight by 2020. As a result, in less than 20 years, the US ports and related infrastructure must be capable of handling more than 50 million TEU's per year³. This projected growth in global trade and an increase in size of container vessels will result in a larger volume of containers being handled at marine terminals and will increase congestion at the terminal and the landside operation.

This congestion not only greatly impedes operations at the marine terminals, but also it affects roadway networks around marine terminals. Of the three major modes of transportation at ports - truck, rail, and vessel - trucking is the dominant mode of

² United Nations economic and social commission for Asia and the Pacific,

http://www.unescap.org/ttdw/Publications/TFS_pubs/pub_2398/pub_2398_ch3.pdf, Viewed Jan 2008. ³ MTS, Intermodal recommendations to Secretary Norman Y, Mineta, Marine transportation system national advisory council, Tennessee, Sep 2005.

transportation moving containers in and out of US marine terminals. Nationwide, trucks move 74% of total freight by value and 67% of freight by weight⁴. Given the current level of congestion and its resulting economic, environmental and social implications, it is evident that action needs to be taken to sustain or even improve the operations in and around marine terminals.

Several solutions have been proposed including improvements at the strategic, tactical and operational level, requiring changes in the fiscal and managerial policies, as well as operating strategies. Selecting the best strategy to deal with current and future problems requires an in-depth understanding of operations and monitors terminal resources efficiently. In this dissertation, the study attempts to pinpoint some of these problems, as noted in the following, and proposes solutions for them.

- a) How gates congestion can be improved efficiently with minimal spending?
- b) How changes in truck gate volume can be estimated and controlled through identifying affecting factors?
- c) How a terminal yard capacity can be monitored and utilized efficiently?
- d) How a terminal yard can improve, sustain, or impede operations at the land and sea side?
- e) How revenue can be increased from an efficient management of existing resources?
- f) How suitable policies can monitor yard capacity and ease the congestion, while generate the revenue stream for terminal operators?

⁴ US census Bureau, <u>http://factfinder.census.gov/servlet/IBQTable?_bm=y&-geo_id=&-</u> <u>ds_name=CF0200A01&-_lang=en</u>, Viewed Feb 08.

1.2 Research Objective and Scope of Work

To tackle the above mentioned questions, this dissertation aims to study the process of moving containers between a wharf (or apron where containers are loaded and unloaded from a vessel) and truck gates in marine container terminals and examines the relationship between the activities in these two areas. Understanding this relationship is important in order to make educated decisions to improve existing conditions and efficiently accommodate the anticipated changes in volumes that will result from the projected growth in global trade and increased vessel size.

The dissertation develops analytical and simulation models to relate sea and land side activities by exploring influential factors in the container dwell time, assessing and estimating the container dwell time, estimating truck volume at gates based on the apron's volume, exploring the impact of truck and apron volume variations on the terminal throughputs, and examining the impact of the establishment of an appointment system to ease the congestion at the terminal gates. Figure 1-1 illustrates main modules used to delineate this relationship.



Figure 1-1: Dissertation framework

The steps taken to maintain the dissertation objective are as follows;

- 1. Truck gates and apron's activities are related by tracking containers from arrival until departure point. Container's Dwell Time (CDT), which is the duration of time that a container stays in a yard, is estimated to establish this relationship (a potential response to the question "b" in Section 1.1).
- 2. Factors influencing the CDT, called herein CDT determinant factors, are identified to assist the author in the CDT modeling. The determinant factors and their effects on the CDT create a relatively strong model which is being utilized in different practical scenarios to measure the effect of changes in determinant factors on the CDT (a potential response to the questions "c", "d", and "e" in Section 1.1).
- Modeling and estimating CDT and apron's container volume provides an underlying knowledge to analyze truck gate volumes (inbound and outbound).
 An analysis on truck gate traffic is also performed to find a potential pattern in

containers arrival and departure. An hourly assessment is also performed to investigate the hourly patterns of container movements at the gates (a potential response to the questions "a" and "b" in Section 1.1).

4. The dissertation validates the findings of analytical modeling techniques in a virtual environment by developing a macro simulation model of a container terminal. Alternative gate and apron designs are also developed to investigate the truck gate performances and terminal throughput in different circumstances (a potential response to the questions "a", "b", and "f" in Section 1.1).

Figure 1-1 shows the developed tasks required to maintain the dissertation objective.



Figure 1-2: Dissertation assignment

Task One: Container Dwell Time (CDT) in a terminal yard

Several factors affect the length of the period over which a container remains in a marine terminal yard (container dwell time). The container dwell time has a direct impact on terminal productivity and overall terminal operations; the yard efficiency can be improved by reducing this time. Alternatively, the extension of this time produces more revenue for terminals by collecting more demurrage fees (a fee assigned to containers remaining in a yard beyond their free time). The qualitative CDT evaluation can assist port operators and decision makers to review their policies and deploy appropriate plans at a strategic and tactical level. This dissertation performs the following tasks to analyze the CDT.

Subtask 1: Identify factors affecting the CDT from a broad range of attributes varying from stakeholders in the supply chain to seasonal demand for cargo.

Subtask 2: Explore data mining algorithms and determine the suitable ones to classify and model the CDT based on its determinant factors.

Subtask 3: Model the CDT based on its determinant factors and find the most robust model for alternative scenarios.

Subtask 4: Investigate the application of the model in practice by initiating different scenarios and estimating a yard capacity and its revenue in each case. This investigation assists policy makers in assessing how changes in the CDT determinant factors can affect the yard capacity, terminal revenue, and truck gate activities.

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Task Two: Relating apron activity and gate truck traffic

Truck traffic at terminal gates depends on the number of import containers discharged from each vessel and the number of export containers loaded onto a vessel. Evidently, there is a link between vessel calls at a terminal and gate traffic. This relationship, however, is not direct, since both import and export containers stay in a yard for a period of time (CDT) as discussed in Task One. Understanding the connection between vessel arrivals and truck gate traffic is essential in order to monitor, control, and estimate gate truck traffic and container volumes at an apron. This knowledge assists terminal managers create appropriate policies at both tactical and operational levels. Gate operations can be optimized to efficiently accommodate the anticipated volume of trucks by allocating the necessary resources. At the tactical level, decisions such as the extension of the gate hours and the establishment of an appointment system may be considered to deal with the excessive congestion during a specific period of time. While different time periods can exhibit unique truck volume patterns at gates, different days of the week may present distinct patterns as well. The recognition of this distinction (i.e. hourly and daily truck volume at gates) assists decision makers in utilizing their resources on a particular day and time, for a specific service, such as the dedication of a number of gates on Friday to service empty containers (more explanation is presented in the chapter four).

This dissertation performs the following tasks to identify the relationship between the apron activities and gate truck traffic.

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Subtask 1: Identify daily patterns of container departure and arrival at gates based on the apron's volume and their CDT.

Subtask 2: Identify hourly patterns of container departure and arrival at gates based on truck gate operation hours.

Subtask 3: Develop alternative scenarios examining the effect of increases in container volumes at the apron and CDT changes on gate volumes.

The outcomes of this task are also utilized in the simulation approach to model the CDT, truck arrival rate, and vessel discharging rate.

Task Three: Terminal's Simulation Operations

A simulation model is developed to examine the robustness of the analytical approaches built in the previous tasks and to visualize the gate and truck interchange operations particularly. The truck interchange area is an area inside the terminal where containers are loaded onto trucks or unloaded from trucks. The simulation model will assist in examining the ability of the gates and truck interchange area to accommodate truck traffic under various scenarios and determine the effectiveness of the proposed strategies to improve gate operations. Such a tool would provide valuable information to terminal operators wishing to determine the anticipated impact of the proposed improvements before their implementation. In addition, this tool could assist transportation planners wishing to understand port related congestion issues and propose solutions to decrease congestion and improve traffic operations in the terminal area. This dissertation performs the following tasks to simulate gates and truck interchange area activities. **Subtask 1:** Extract requisite information from various resources (historical data, common use and literature).

Subtask 2: Build the base case scenario by simulating the gates, the truck interchange area, the yard, and the apron operations. This task simulates the port operations using the common port practices described in the following chapter.

Subtask 3: Evaluate the port performance factors for the base case scenario.

Subtask 4: Establish different scenarios such as changes in vessel and truck traffic volume and evaluate the terminal performance factors in each scenario.

Subtask 5: Propose and implement an appointment system at the gates and the truck interchange area.

Subtask 6: Analyze the terminal performance factors for the proposed system and investigate the efficiency of different scenarios by comparing these factors.

1.3 Contribution of this dissertation

Relating the terminal gates traffic to the apron's activities, the dissertation objective, has been initiated to mainly provide a product to assist terminal operators in their policy making decisions. Therefore, analytical and simulation models, data mining algorithms, and pattern recognition process, which are developed throughout the dissertation and exercised on the observed data have presented findings that benefit decision makers to improve or sustain current congestion at terminals. Considering this initiative, this research establishes two approaches to maintain its goal; theoretical and practical. From a theoretical standpoint, to the best of the author's knowledge, this work is the first attempt to relate the gate truck traffic and apron activities by identifying factors that not only could model and estimate truck gate traffic based on apron activities, but also utilize these factors to estimate container dwell time, yard capacity, and terminal revenue obtained from demurrage fees. This analytical assessment is a novel approach in using container's data commonly collected by terminal operators to establish a noble connection between various elements involved in container's handling (e.g. ocean carriers, container's status) and terminals physical and economical aspects. The developed model can be used to develop and evaluate policies for easing truck congestion at terminal gates. It also measures the impact of these proposed plans on yard capacity and revenue. This is a vital contribution since previous studies (Hoffman 1985, Huynh et al. 2005, Merckx 2006, Al-deek 2001, Gambardella et al. 1998, sideris 2001, Klodzinski et al 2003, Ioannou et al 2002, Alessandri 2004) evaluate the effect of plans on one part of the system without considering the effect on the entire system.

From a practical operational point of view, the developed simulation model can assist in better understanding current and future conditions, understanding the impact of the proposed improvements before an investment is made such as the potential impact and the effectiveness of a gate appointment system. Different innovative scenarios examined in this developed model are as follows:

- How the CDT changes affect terminal performance factors (e.g. Truck turn time) and the terminal's gate traffic,
- How the volume changes (at the apron and gates) influence terminal performance factors,

• How the proposed appointment system at the gates and truck interchange areas affects the terminal performance considering various levels of demand (i.e. truck volume) and operation time periods (i.e. peak hours). This system which has currently been utilized at the gates of some terminals has not been studied and established in truck interchange areas. In addition, no study has been found to investigate the efficiency of the utilization of this system at the gates and the truck interchange area in different time period, i.e. peak and slack time period.

1.4 The dissertation organization

The dissertation is organized as follows: Chapter 2 reviews the terminal operations and the container handling procedures at terminals. Chapter 3 reviews literature on a broad range of port operations, modeling techniques and simulation systems is presented in chapter three. Chapter 4 presents a developed model to estimate the container dwell time using a set of determinants. Chapter 5 covers the procedure of estimating truck gates traffic based on the vessel traffic at aprons using analytical techniques. Chapter 6 presents the development of the simulation model to estimate the truck gate volume based on the container volume at the apron. Finally, chapter 7 summarizes the work performed, presents conclusions, and provides recommendations for future studies.

Chapter 2 BACKGROUND – INTERMODAL FREIGHT TRANSPORTATION PROCESSES

2.1 Introduction

Intermodal transportation which provides an efficient way of cargo handling throughout Global Supply Chains (GSC) initiates from a shipper's node and ends in a receiver's node. A GSC consists of multiple firms, both upstream (i.e. supply) and downstream (i.e. distribution) and the ultimate consumer. Typically, two types of flows can be traced through the GSC: data flow and cargo flow. Data flow relates to the exchange of information between involved stakeholders, managing the container handling procedures and providing the seamless operations throughout the GSC. Cargo flow presents the physical movement of cargo through the nodes and links in the GSC network (illustrated in Figure 2-1).

Generally, shippers, who make decisions on the movement of freight in the region and generate trips from an origin to the destination point, are the set of economic agents including shipping department of manufacturing firms, distribution agent, and freight forwarder (Harker, 1985). Depending on the geographic location of the origin and destination in the GSC, the cargo may just utilize land transportation (e.g. common trading practice between the NAFTA countries). In most cases, however, water transportation is used within the GSC network to transfer containers from an origin to a destination port. Among all transportation modes, water transportation transfers 78% of US international merchandise trade by total weight followed by truck transportation with

11%⁵. Ports as main nodes in the GSC typically receive containers via land from the carriers in the origin country loaded onto a vessel to be hauled to the destination marine port. After containers arrive at the destination port, they are transferred to one of the inland modes of transportation (motor carrier, rail, or barge) to be hauled to the receiver nodes or distribution centers and end their journey. As illustrated in Figure 2-1and emphasized before, this dissertation will study the procedure of container handling taking place in marine container terminals.



Figure 2-1: The general procedure of cargo hauling throughout the GSC

Typically, export containers are delivered to the marine terminal by rail or truck (land side) and stored for a period of time at the yard before being loaded onto a vessel (sea side) to be shipped to the destination port. Import containers are unloaded from a vessel (sea side), stored at the yard and loaded, typically, onto truck or rail (land side). Therefore, excluding transshipment volume, containers move among three major areas in

⁵ Bureau of Transportation Statistics, US international trade and freight transportation trends, US Department of transportation, 2003.

the marine terminal: sea, yard and land side. Figures 2-2 and 2-3 illustrate these procedures for export and import containers along with the direction of container movements. A detailed description of the tasks performed in each area and the equipment utilized in each area will be discussed in the Sections 2.2 - 2.4 below.

Data also flows between terminal operators and truck, rail, and vessel carriers simultaneously or even before containers reach the port, to provide a seamless and secure operation. This information is processed by terminal operators and any faulty or missed information is reported back to the related parties for correction. The direction of data flow between the three areas is illustrated with dashed lines in Figures 2-2 and 2-3. Since any incomplete information may delay vessel loading and unloading procedures at the wharf, or delay a truck processing at the gates, this chapter presents a brief review of the official paper work typically processed by US ports.

Finally, whereas decision makers and port operators are much interested in evaluating the port performances and potentially examine new ways to improve them, the factors that measure the berth, yard, and land productivity and performance are introduced. These parameters assist the author in analyzing different scenarios (in the simulation layer) and propose recommendations to improve the gate and truck interchange efficiency. More discussion on these parameters will be presented in chapter 6.





2.2 Sea side operations

A vessel arrives at a port and berths at the quay typically based on a defined schedule (berth scheduling). Depending on the length of the quay, berths usually accommodate a number of vessels. The berthing time and the exact position of each vessel at the quay, as well as various quayside resources are determined, when berth allocation and usage planning are performed. Vessel loading and unloading is a time consuming procedure which fluctuates from hours to days depending on the vessel size and the operational processes. The vessel size varies from deep sea vessels with a loading capacity up to 13,000 TEU to feeder vessels with a capacity up to 4,000 TEU⁶.

Typically, the loading a vessel must obey the stowage planning which is designed by vessel carriers and executed by port operators. The container stowage planning concerns the suitable placement of containers in a container-ship on a multi-port journey, which requires consideration of the consequences of subsequent ports (Wilson et al., 2000). The placement of containers in a cellular vessel is performed with respect to the vessel structure and operational restrictions to minimize reshuffling. Containers are loaded or unloaded from a vessel by quay cranes, mobile container cranes, or gantry cranes (single/ double trolley). The number of quay cranes working on each vessel depends on the vessel size and crane availability. Normally, two to five cranes operate on deep-sea vessels, and one to three cranes on feeder vessels. Cranes may perform double–cycling during the loading or unloading a vessel. Loading ships as they are unloaded is called double-cycling, thereby improving the efficiency of quay cranes (Goodchild et al., 2005).

⁶ Global security, <u>http://www.globalsecurity.org/military/systems/ship/container-types.htm</u>. Last viewed Feb07.

Documentation

From a legal action point of view, several documents have to be filed prior to the vessel arrival. Notice of Arrival (NOA) is required by the US coast guard 96 hours prior to the vessel arrival. Although this notice is usually given 24 hours in advance, there is an increasing pressure to impose the 96 hour requirement. More discussions on the vessel's arrival documentation can be found in Petrakakos (2005) dissertation.

Prior to the vessel departure, the BoL and custom form 1300 is resubmitted. In addition to the legal paper work, some issues may also arise with voyage orders before vessel departure. In most cases, voyage orders are sent two weeks prior to the vessel departure. There are, however, some cases in which the information is remitted a day prior to the vessel departure. In these cases, the problem can escalate when there is a trouble with the sent information such as missing or incomplete information, or inaccuracies in data entry. Consequently, the vessel departure may be delayed to resolve the issues.

2.3 Yard side operations

After containers are loaded and parked in the yard, they are allowed to stay in the yard free of charged for a period of time. After exceeding this "free time", a daily demurrage fee is applied to containers. The duration of time that containers spent parked in a yard is called the container dwell time, and is a key evaluation factor in the analysis performed in this dissertation.

Containers are stored and stacked in different yard zones based on given plans prepared by port operators. Terminal yards are usually divided into different zones dedicated to import, export, empties, and reefer (refrigerator) containers. Import zones are mostly located close to rail, truck gates, and truck interchange area (except transshipment containers). On the other hand, export zones are mostly located close to the apron, as illustrated in Figure 2-4.



Figure 2-4: Import & Export Zones

Empty containers are usually located close to a rail yard and/or truck gates, although the characteristics of a terminal, port policies, and the volume of empty containers play a vital role in locating them in or out of the terminals. Some ports designate an area outside of the terminal as an empty depot for empty containers to ease the congestion in terminals and at gates.

Equipment

Containers are stacked in the yard by stacking equipment (e.g. gantry cranes, straddle carriers, reach stackers) in different blocks and accessible by their row, bay and tier
numbers, as shown in Figure 2-5. The number of rows, bays and tiers depends on the type of equipment used in the terminal.



Figure 2-5: Container's stacking area in a yard with defining tier, row and bay, extracted from Ilaria Vacca (et al., 2007)

A variety of equipment is designed to handle two major tasks in a storage yard area: intra-terminal transferring and stacking. Equipment transferring containers from the apron to the yard and from the yard to the apron includes Shuttle carriers, Tractor/trailers, Multi-trailers, and Automated Guided Vehicles (AGV). Equipment performing container stacking are Rubber Tyred Gantry crane (RTG), Rail Mounted Gantry crane (RMG) and Overhead Bridge Crane (OBC) or Automated Stacking Crane (ASC). Some equipment can be considered both as prime movers and stacking such as Straddle Carriers and Reach Stackers (for small size terminals). Front end loaders, Top loaders (handlers), and Forklift trucks handle empty containers and help the ancillary movements.

Depending on the port characteristics and equipment, four mechanisms of container handling can be initiated in marine terminals: 1) Chassis system, 2) Straddle carrier direct system, 3) Yard gantry system and 4) Straddle carrier relay system (Theofanis et al. 2008). Figure 2-6 illustrates these transferring systems. A brief description of each system is discussed in the following:

- In the chassis system, containers that are unloaded from the vessel by cranes and dropped onto a chassis that is pulled by truck-tractor. They are driven from the apron to the yard and left stored with their chassis underneath them. Although this system increases container handling performance, it requires considerable terminal space which is not typically available in the majority of cases.
- In the straddle carrier direct system, straddle carriers perform all transferring (from an apron to a yard, a yard to truck gates or a rail yard and vice versa) and container stacking.
- In the yard gantry system, containers are transferred to a yard from aprons, truck interchange area, and rail yards by transferring equipment. Containers are stacked and withdrawn from the yard by gantry cranes. One row in a yard block is dedicated for loading and unloading a trailer by gantry cranes.
- In the straddle carrier relay system, containers are transferred from an apron to the yard by tractors/trailers; straddle carriers stack containers and also transfer them to the truck interchange area or a rail yard. It is important to note that straddle carriers cannot perform stacking more than three containers high. Therefore, this system is a practical system for small to medium size container terminals.



Figure 2-6: Transferring systems in container marine terminals (concept derived from -

Boile 2006)

2.3 Landside Operations

On the land side, containers arrive by train or truck and are loaded or unloaded by one of the equipment dedicated for transferring. The mechanism of loading or unloading depends on the system in place. In rail, containers are assigned to a particular wagon depending on their weight, destination, and type. In following, the procedures of loading and unloading trucks are discussed elaborately.

Export Procedure

Typically, trucks arrive at a terminal to pickup import, drop off export containers, or both. When a truck arrives with an export container (full or empty), the container's serial code (container number), and its weight and condition are checked at the terminal gate. If the driver's paper work is valid and the container's condition is acceptable, then a space in the interchange area or a particular row in a yard is assigned and the truck is cleared to proceed into the terminal. The truck proceeds to the assigned area and releases its load (empty or full container). If the truck is assigned to pick up another container, it stays in the area for the loading procedure or moves into a different area in the yard to pick up its load. Every export container has a defined schedule to be loaded onto a vessel. Nevertheless, the exact loading time can fluctuate, due to the decision of ocean carriers. Figure 2-7 demonstrates the embarkation procedure of export containers from truck gates to a vessel.

Import procedure

When a truck arrives at a terminal to load an import container, a logistic associate verifies that the container has been released by the ocean carrier and that no other holds exist on the container (e.g. USDA inspection, Customs, etc). If there is a problem with the paper work (e.g. wrong container number), the trucker is sent to the customer service to solve the problem. If everything is valid, an interchange or yard area is assigned and the truck is clear to proceed into the terminal. In the truck interchange system, the assigned container is transferred from the yard and loaded onto the truck. In the gantry crane system, the truck may go to the defined area in the yard and the container is loaded by the gantry crane. Figure 2-8 presents the handling procedure of import containers.







an import container

A truck may unload an export container and load an import container on the same trip. In this case both processes are performed.

2.4 Container Terminal performance

Key factors in measuring marine terminal performance are: 1) productivity, 2) utilization, and 3) service rate (Theofanis et al., 2008, Le-Griffin et al., 2006). Table 2-1describes commonly productivity measures in container terminals.

Table 2-1: Common productivity measures in container terminal (concept derived from

	Productivity	Utilization	Service rate
Crane	Moves per crane-hour	TEUs/year per crane	
Berth		Vessels/year per berth	Vessel service time (hrs)
Yard	TEUs/Storage Acre	TEUs/year per gross acre	
Gate		Gate throughput (Containers/hour/lane)	Truck turn time

Le-Griffin et al., 2006)

For seaside operations, the quay crane and berth productivity are major factors. A maximum nominal quay crane performance is about 50 to 60 moves per hour, although these numbers decrease to 20 to 30 moves per hour in practice. Vessel turn time is one of the factors measuring berth productivity. The vessel's turn time is the time between a vessel's arrival and departure. This time includes waiting time, *the time between vessel arrival at the port and movement from anchorage*, berthing time, *the time between vessel movement from anchorage to a berth*, service time, the *time between vessel berthing and leaving the berth*, and sailing delay, *the delay between vessel leaving the berth and leaving the port*.

On the yard side, the average number of containers per area unit per time unit defines a yard performance or utilization. Average yard performance for transshipment hubs,

gateway ports, regional ports and feeder ports are 28.3, 18.2, 11.3 and 3.2 thousand TEU per hectare per year respectively (Theofanis et al., 2008). Obviously, the container dwell time is a major factor impacting the yard performance. From an operational point of view, port operators are also interested on the gantry crane utilization. The operational performance of gantry cranes is about 25 moves per hour.

On the land side, gate and truck interchange area performances are the key factors which are measured by truck turn time. Truck turn time is a time between a truck's arrival and departure at the gates. This time includes the truck's arrival at the gate, a driver's service at the reception counter, the truck's arrival at the interchange area, the truck's leaving the interchange area, the truck's arrival at the exit gate, and the truck's leaving the gate. Though, the queue behind the entrance gates is not included in the truck turn time estimation, it indirectly affects the gates and the truck interchange area performances.

2.5 Conclusion

The objective of this chapter is to present a brief introduction on 1) how cargos are handled in a marine container terminal; 2) what operations are executed to service a container from land to water and vice-a-versa; 3) which parties are involved in this operations; and 4) how terminal's efficiency is rated in a container terminal. Having this knowledge will be critical to understand the study's approaches in maintaining the dissertation objective.

Upon reviewing a marine container terminal as a system, the study observed that different subsystems can be initiated (i.e. Land, yard, and sea) each included different elements with different characteristics. Nevertheless, each subsystem and its operations is affected by other subsystems in a great extend. This is a major area of interest in the current work.

Next chapter are provided literature review demonstrating how researchers attempts to improve containers handling in different perspective from optimization, promoting the utilization of high-tech tools to modeling and predicting future behaviors.

Chapter 3 LITERATURE REVIEW

3.1 Introduction

Exhaustive review of literature identified many articles that deal with marine terminals at a strategic, tactical, and operational level using analytical modeling or simulation techniques. In this chapter, those articles are reviewed and presented in the task order stated in Chapter 1. In the first Section, literature focusing on the CDT and its determinant factors along with the effect of the CDT on port and yard performance is presented. Literature discussing gate and wharf connections are presented next, followed by literature on the optimization of terminal operations (from land to sea side). Articles concentrating on truck gate activities and the implementation of an appointment system at gates are reviewed in the last Section.

3.2 Container dwell time and its determinant factors

A literature review on the calculation of container yard using CDT revealed that two approaches can be drawn; demand and supply approach (Chu et al., 2005). Hoffman (1985) developed an equation to estimate the required storage yard area as a function of the CDT, the number of containers handled per year, the height of the containers stacked, and the peak-hour. Based on this developed formula, he concluded that the land area needed for a container yard can be estimated for a specific demand. More elaborations on this developed formula are presented in the following chapter. From demand approach, UNCTAD (1985) developed some container terminal-planning charts accompanied with developing algorithm to estimate the container park area needed for port planners.

From supply approach point of view, Dally (1983) developed another equation to estimate annual yard capacity using the CDT, the number of container ground slots, mean profile height, and working slots in the container yard. The developed formula estimates the number of containers a container yard accommodated on the basis of a given yard space. This formula is demonstrated in the following chapter as well. The dissertation utilized this developed formula to estimate terminal yard capacity based on the CDT variations. Dharmalingam (1987) modified Dally's equation by introducing a slot utilization factor. In his equation, the annual yard capacity can be calculated using the production of the total number of available slots, slot utilization factor, and the result of the division of a number of days per year by the mean of container dwell time.

There has been relatively little research that focuses on the CDT and its determinants factors. Merckx (2005) discussed the impact of dwell times on container terminal capacity and provides a theoretical framework of constraints that a terminal operator has to take into consideration. He described the different dwell time charging schemes on containers and summarized a number of pricing mechanisms available to terminal operators to optimize the terminal capacity. In conclusion, he defined a general guideline to implement a terminal charge which affects the dwell time so that the available quay and gate capacities are optimized.

In another literature, Merckx (2006) tried to optimize container terminal capacity through container dwell time charges. He introduced parameters influencing the storage yard

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capacity, i.e. yard area, handling system, container dwell time, and stacking height. By concentrating on the CDT, he utilized Dally's equation to observe the effect of dwell time changes on the storage yard capacity. He performed a sensitivity analysis to determine the impact of the CDT reductions on the yard capacity. Finally, he concluded that his approach resulted in a much higher storage yard capacity.

In the same manner, Rodrigue (2008) discussed the interaction of logistic players with different interests in sea port terminals. He argued that freight forwarders, on one hand, are using terminals as an extended component of their distribution centers and making the best use of the free time available in seaport. On the other hand, terminal operators are also reacting to the changes in supply chain management practices by imposing restrictions in terms of dwell time and conditions to terminal access. Finally, he found out that the extension of the gate hours can help reduce the container dwell times at seaport terminals.

Using a different approach, Huynh (2008) introduced a method to evaluate the effect of the CDT and storage policies on import container throughput, storage density, and rehandling productivity. He considered two import storage strategies: 1) non-mixed- no stacking of new import containers on top of old ones and 2) mixed –stacking. For a non-mixed storage policy, it was found that the increase in CDT lowered throughput while it increased re-handling productivity. For the mixed storage policy, the increase in CDT raised throughput but decreased re-handling productivity. Monte Carlo Simulation (MCS) was used to further estimate the expected number of rehandles to load an import container onto a truck.

Considering the aforementioned studies and with the help of actual data, this study extends Merckx analyses and delineates more factors affecting the CDT. To probe how CDT changes affect yard capacity and terminal revenue, the study utilizes Dally's formula.

3.3 Gate and wharf Correlation

Sideris et al. (2001) implemented dynamic and static models on the number of inbound and outbound containers to forecast daily demand at a container terminal by relating truck gate traffic and vessel activities. Upon the implementation of their model and compared with the historical data, they observed that the dynamic model (predefined time diagram) provided a better fit of the forecast values to the observed distribution (based on the probability distribution) particularly for export containers.

To manage and optimize container movements, Alessandri et al. (2004) analyzed container handling procedures in inter-modal container terminals using feedback control. They proposed a model, made by a set of container queues inside a terminal and captured a dynamic aspect of the system by means of discrete-time equations. The optimization problem was posed as an optimal control problem based on the minimizing the transfer delays of containers in the terminal. A receding-horizon scheme was implemented to solve their control problem (minimizing transfer delay). However, the model was not tested against the observed data to validate and investigate the robustness of the developed model. Gambardella et al. (1996) forecasted day to day export operations in a container terminal. They employed an ARIMA (auto regression integrated moving average) model to predict a number of containers to be loaded onto a vessel. The number of containers arriving by truck was modeled by a local regression model. Then, both

outcomes were combined to reflect the number of loaded containers into a ship versus the number of containers arriving by truck. By the integration of the forecast model into their developed simulation module, they were able to simulate day by day terminal operation in near future.

With the intention of modeling and predicting freight movements around sea ports, Al-Deek (2001) proposed two approaches: linear regression and Back Propagation Neural Networks (BPNN). The linear regression model provided reasonable results. However, an assumption of grouping weekdays and weekends had been made. Therefore, the results did not demonstrate daily truck movements. He used historical data to derive daily truck volumes. BPNN was also employed on the existing data without any assumption and criteria limitations. T-test and Kolmogorov-Smirnov normality test indicated, with 95% confidence level, no significant differences between actual data and the models' outputs. Conclusively, he recommended the BPNN model as a superior tool for the prediction of truck volume around a Florida port. The port was handling containers, bulks, liquids, and break bulk commodities. With the same objective, Klodzinski et al. (2005) executed two neural network models to generate truck trips around another sea port in Florida by using vessel freight data: Fully-Recurrent Neural Network (FRNN) and BPNN. The port had insignificant number of container activity and significant liquid commodity shipments. The BPNN model was robust with 95% confidence level and it also captured seasonal truck data. Nevertheless, in developing the BPNN model, the import data (liquid commodities) was distributed evenly over the entire month. The FRNN model was developed without any requirement of distributing data, which was a big advantage of this model, however, it failed to produce a good result due to the lack of an adequate data. Conclusively, the author recommended the FRNN model when adequate data are available.

With respect to these studies and to relate truck gates and wharf activities, this research establishes another approach to link gates through traffic and the apron's container volume. This study defines the apron's activities as an initiating point and the day containers arrived or departed at gates is defined as an end point. The CDT is modeled based on factors influencing the CDT. Then, the CDT pattern will be discerned in departing or arriving containers on a daily (weekday and weekend) base. Derived from the distribution pattern, daily truck gate activities are estimated for weekday and weekend.

3.4 Terminal operations and task optimizations - Simulation approach

In regard to the task optimization and resource allocation in container terminals, many studies have utilized simulation as an evaluation technique. Simulation is not only a suitable tool to handle relatively complex object, but also provides a good representation of terminal procedures in a user friendly environment understandable by most decision makers. Numerous researchers have also utilized analytical approaches to reach this objective.

Won et al. (1999) proposed an object oriented simulation model using SIMPLE ++ to analyze port performance. Object-oriented simulation software is chosen, since it easily can be modified or extended. They validated their simulation model comparing with the observed data extracted from one Korean terminal. They claimed that the developed simulation model were robust enough to examine some practical scenarios such as increase in a number of container in a terminal, or examining the efficiency of gantry cranes in handling containers. Liu et al. (2004) investigated the impact of automation and terminal layout on a terminal's performance. They considered three different scenarios: manual operations, and automated terminals with two different terminal layouts. By utilizing the "Mathlab", "Simulink", and "Stateflow" as a simulation package, they concluded that Automated Guided Vehicles System (AGVS) could substantially increase a terminal's throughput without any regard to terminal layouts. Merkuryeva et al. (1999) simulated terminal operations using ARENA software application with the objective of measuring terminal performance in different scenarios such as different yard layouts, various weather conditions, and various utilizations of terminal resources. They offered the web based simulation model to give users the capability of remote accessing. With the objective of developing a decision support system at a port, Murty et al. (2005) introduced a variety of inter-related decisions made daily by port operators to minimize the berthing time of vessels, estimate required resources to handle workloads at ports, and evaluate truck delay time and analyze congestion on roads, storage blocks, and docks inside terminals. They designed and solved their decision support system model with a mathematical approach.

Sgouridis et al., (2003) utilized simulation software to measure terminal performance in straddle carrier container terminals. They analyzed different yard operation rates and gate service rates for two extreme scenarios (Slack & Intensive). Their study revealed that there would be no considerable impact by either increasing arriving volume or decreasing yard service rate in a slack scenario (low service ratio). Nevertheless, changes on gate service rates remained quite sensitive. They also determined that the truck turn time

would be improved if truck traffic disseminated evenly during work hours and terminals adopted the semi-automated management system.

By optimizing an overall port performance, Rashidi et al. (2006) classified and formulated terminal operations into five scheduling decision systems: Berth & Quay crane allocation, storage space assignment, rubber tiered gantry crane, scheduling and routing internal vehicles, and appointment assignment to external trucks. For assigning appointment times to external trucks, the objective function was to minimize the terminal gate costs. They suggested two frameworks for solving their problems without, however, applying them to solving the problems.

This dissertation draws similarities with the simulation module structures found in the literature, particularly the work by Won et al. (1999). The system architecture of this study and Won are similar in some areas including the gates and the apron.

3.5 Gate congestion and an appointment system

Land operations in marine container terminals can be related to rail yard operations, gate through traffic, and truck interchange services. Maksimavicius (2004), who studied the optimization of freight processing time in a Ro-Ro terminal also examined the capacity of terminal gateways. He found out that the increase in the number of gateways would not necessarily improve total freight processing time, as long as the terminals' accommodating policy remained insufficient. Juang et al. (2003) evaluated delays at marine gates. They found out that improving the service rate at gates was a much more effective than increasing working hours. Also, they claimed that terminals had to utilize advanced technologies to improve gate services before reaching saturation.

In practice, truck traffic at gates is mostly concentrated during the day, particularly during the peak hours (Meyer et al., 2004). This concentration causes heavy congestion on the roadway networks around terminals especially close to the urban areas. Prior to 2003 in California, terminals closed their gates at 2:00 PM to address trucks in queues before gate closing (Roche Ltee consultant, 2006). Port facility capacity goes over utilization in some periods and under utilization for the rest of hours. Obviously, two important impacts can be obtained by encouraging truck companies to move their trips from peak to non-peak hours: congestion mitigation around marine roadway networks and increases in port performances (e.g. truck turn time).

To ease the gate congestion, one of the proposed recommendations is the implementation of an appointment system at in-bound gates (EPA, 2007). In the beginning, truck drivers appeared to have a positive approach toward this proposal, mainly because truckers are paid by their loads, not by their spent hours. Hence, if the appointment system reduces trip times, truckers have every incentive to use it (Giuliano et al., 2006, Roche Ltee consultant, 2006). However, after implementation of this system in the LA port, truckers did not give a satisfactory rating to this effort. Based on a conducted survey, most truckers believed that the appointment system would simply shift the queues to inside the terminals (Giuliano et al., 2006).

This result revealed that the appointment system can be successful if it is integrated into the terminal operating system. If terminal operators know in advance which containers will be picked up or dropped off, they can better manage truck flows and container movements inside the terminal (Giuliano et al., 2006). Stimulating from this fact, the study recommends the establishment of an appointment system at the truck interchange area.

To promote the establishment of an appointment system at terminal gates, Guan et al. (2009) analyzed the congestion at marine terminal gates using a multi-server queuing model. An optimization model was developed to minimize truck waiting costs at gates. The model was tested using data from field observations. The results indicated that truck waiting costs at marine terminal gates was an issue that needed to be addressed. To address this issue, they proposed a truck appointment system to reduce gate congestion and increase system efficiency. Finally, they concluded that an optimized appointment system can reduced the total system costs, especially truck waiting cost.

With the objective of reducing truck turn time, Huynh et al. (2005) recommended implementing an appointment system at entrance gates. They evaluated the maximum number of trucks with appointments for each defined zone and time window, such that the average truck turn time did not exceed a maximum. They also considered different scenarios in their formulations for the percentages of tardiness or truck absences. They solved their problem by applying ad-hoc heuristic techniques. He concluded that implementing a truck appointment system is not always an effective solution. The results suggested that truck appointment system can be effectively implemented, if its parameters (e.g. number of trucks per time period) are determined efficiently.

In the same theme, Huynh (2009) performed the evaluation study on a critical component of the truck appointment systems (scheduling rules). The objective was to analyze how the various scheduling rules affect resource utilization and truck turn time in grounded operations. He proposed two types of appointment scheduling strategies (1) individual appointment systems (IAS), and (2) block appointment systems (BAS). He utilized a simulation technique to determine the effectiveness of the scheduling strategy. He concluded that there is a clear benefit for a terminal without an appointment system to employ the IAS. Such a scheduling system kept the yard cranes highly utilized while improving the internal yard turn time by about 44%. In addition, he claimed that the IAS could still be an effective solution when a good portion of trucks are walk-ins, no-shows, or late considering the proper spacing between appointments.

The dissertation expands Huynh and Walton's works (2005) and establishes an appointment system at the interchange areas as well. To the best of our knowledge, no literature exists to examine an appointment system at the truck interchange areas. The establishment of an appointment system at the interchange area and truck gates is expected to not only reduce truck turn time, but also reduce truck gates congestion. However, as researchers emphasized on their studies, an appointment system can be a cost effective solution when it is determined and established in the right time and places. The author finds no literature that investigates thoroughly on this issue. This is also an interesting subject that this research attempts to address by initiating different scenarios in the developed simulation model.

3.6 Summary

Table 3-1 summarizes the aforementioned studies including their objectives, important outcomes, and applied modeling techniques.

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			Planning	Modeling	Important
Subject	Author	Objective	level	Approach	outcomes
Container dwell time and its determinant factors	Merckx (2006)	Impact of container dwell times on container terminal capacity	Tactical-	Data-Driven analysis	Decrease of container dwell time increases terminal capacity
Container dwell time and its determinant factors	Hoffman (1985)	Container Facility planning	Strategic	Mathematical	The estimation of the required storage yard area as a function of CDT
Container dwell time and its determinant factors	Dharmalin gam (1987)	Design of storage facilities for containers	Strategic	Mathematical	Develop an equation to initiate a slot utilization factor
Container dwell time and its determinant factors	Merckx (2005)	Optimization of container terminal capacity through dwell time charges	Strategic	Mathematical	Introducing influential parameters in the storage yard capacity
Container dwell time and its determinant factors	Huynh (2008)	Evaluate the effect of container dwelling and storage policies on import container throughput	Tactical	Monte Carlo Simulation	Two storage policies were identified: non- Mixed and Mixed
Container dwell time and its determinant factors	Rodrigue (2008)	Terminalization of supply chains	Tactical/ Strategic	Policy approach	Conflicting interests of port operators and freight forwarders in the use of a terminal yard

Table 3-1: Literature review summary

Subject	Author	Objective	Planning level	Modeling Approach	Important outcomes
Gate and wharf interrelation	Sideris et al. (2001)	Dynamic estimation of daily container movements	Tactical	Statistical	Comparison between static and dynamic models
Gate and wharf interrelation	Alessandri et al. (2004)	Minimizing total container transfer delays at a terminal	Tactical	Receding Horizon	Investigation of container transfers between vessels, trains, and trucks
Gate and wharf interrelation	Gambardella (1996)	Forecast export containers volume	Tactical	ARIMA- Local regression	Truck prediction based on vessel volume
Gate and wharf interrelation	Al-Deek (2001)	Predict freight volume around marine terminals	Tactical	Linear regression - BPNN	Truck prediction based on vessel volume for break bulks, bulks, containers, and liquid commodities
Gate and wharf interrelation	Klodzinski et al. (2005)	Predict freight volume around marine terminals	Tactical	FRNN- BPNN	Truck prediction based on vessel volume for containers, break bulks, and liquid commodities
Terminal operations & task optimization	Won et al. (1999)	Optimize terminal operation	strategic- Tactical	Simulation (Simple ++)	Three distinguishing areas for port simulation; gate, yard, berth
Terminal operations & task optimization	Liu et al. (2004)	Evaluation of use of automation in a terminal's performance	Strategic	Simulation	The number of gates and cranes calculations to service inbound trucks.
Terminal operations & task optimization	Merkuryeva et al. (1999)	Measure port performance in different scenarios	Strategic- Tactical	Simulation- Arena	Web based simulation model

Subject	Author	Objective	Planning level	Modeling Approach	Important outcomes
Terminal operations & task optimization	Murty et al. (2005)	Developing a decision support system	Strategic- Tactical	Mathematic (integer programming)	Establishing an automated decision support system to make proper decisions for multiple areas in terminals
Terminal operations & task optimization	Sgouridis et al. (2003)	Measure Container terminal performance	Tactical	Simulation- Extend software	Improving truck turn time
Terminal operations & task optimization	Rashidi et al. (2006)	Optimize overall terminal performance	Strategic	Formulation without solving	Operations in a terminal is divided into five scheduling decision system: berth, storage, crane, internal and external trucks
Gate congestion and an appointment system	Maksimavici us (2004)	Estimate a number of gateways in Ro-Ro terminals	Strategic- Tactical	Statistical- Queuing Theory	The increase of number of gateways does not improve freight processing time
Gate congestion and an appointment system	Juang et al. (2003)	Evaluate delays at marine terminal gates	Operational -Tactical	Statistical- Queuing Theory	Improving the service rate at gates
Gate congestion and an appointment system	Huynh et al. (2005)	Reducing truck	Tactical-	Ad- hoc Heuristic & Simulation	Investigation on the number of yard cranes and proposing an appointment system to maintain objective

Subject	Author	Objective	Planning level	Modeling Approach	Important outcomes
Gate congestion and an appointment system	Huynh et al. (2009)	Reducing truck turn time with appointment scheduling	Tactical- operational	Simulation technique	Investigate the effect of different appointment system scheduling techniques on yard crane utilization
Gate congestion and an appointment system	Guan et al. (2009)	Modeling truck gate congestion and truck gate congestion	Tactical- operational	Multi server Queuing theory	Truck appointment system can reduce truck waiting cost

3.7 Conclusion

The chapter provided a brief review on current literature focusing on container dwell time and factors affecting this time, gates and wharf activity correlation, task optimization in terminal operations, and easing gate congestion through the establishment of an appointment system. The objective of this review was to comprehend and extend the current works through defining gaps and addressing them in some extends. The review revealed that not many research have been carried out on factors affecting container dwell time, which influence the yard capacity, gates and wharf traffic, and revenue earned from the demurrage fee. As one of the contributions of this study, the dissertation will expand these works through developing an analytical model relating CDT determinant factors and CDT. In reviewing literature on gates and wharf correlation, the studies established this correlation through analytical and simulation approaches. This study creates this relation through the utilization of CDT pattern found in vessel and truck loading/unloading containers at the wharf and gates. Finally, studies are reviewed on the optimization of terminal operations through simulation technique; since the current study utilizes the same technique to ease congestion at truck gates through the establishment of an appointment system at the gates and the truck interchange area.

Chapter 4 A model to Estimate Container Dwell Time using a set of determinants

4.1 Introduction

The previous chapters 2 and 3 reviewed the current practices at container terminals and review relevant literature that will be used in some extent in this dissertation.

This chapter attempts to develop an analytical technique to probe attributes assigned to each container dwelling in a terminal which may present a complex relation in nature, though we will probe and discover these relationships to be utilized in monitoring the yard capacity and developing proper CDT reduction strategies.

Factors influencing CDT called herein CDT determinant factors vary from the characteristics of supply chain participants and seasonal characteristics of the goods to the physical location of a terminal (Merckx 2006, Merckx 2005, Rodrigue 2008). The dissertation presents these factors and provides a brief discussion of how they may impact CDT. To examine the impact of CDT determinant factors on CDT, the dependency investigation between CDT and these factors is performed by delineating the percentage of appearance of each factor in different classes of CDT. Upon deriving the correlation between CDT determinant factors and CDT, the CDT modeling is performed utilizing several Data Mining (DM) algorithms on the observed data. After defining modeling performance factors, the robust DM algorithm is chosen and utilized to estimate CDT based on changes in some CDT determinant factors (container's status, terminal's schedule of operations, and ocean carriers). The container terminal capacity

and the revenue earned from the demurrage fees are calculated using CDTs estimated through the developed model.

This chapter is organized as follows. The subsequent section, Section two, presents a description of the factors affecting CDT. Section three elaborates on the observed data utilized in this study. Section four evaluates the characteristics of determinant factors, i.e. factors affecting CDT. Section five provides an overview of data mining algorithms that can potentially be used to draw the relationship between CDT and its determinant factors, and model CDT. Section six presents the methodology and model formulation. Section seven presents a case study examining the dependency analyses between CDT determinant factors and CDT, applying DM algorithms on the observed data, and comparing their results to select the robust model. The selective model, then, is deployed in various scenarios exploring the effect of changes in CDT determinant factors on CDT and ultimately yard capacity and terminal revenue. The last section includes a summary of findings and concluding remarks.

4.2 Determinants of Container Dwell Time (CDT)

Containers arriving at marine terminals are temporarily stored in the terminal's yard before loaded to their next mode of transport. The time period these containers stay in the yard, referred to as CDT, is influenced by several factors. This section provides an overview of factors influencing CDT. These are identified through the literature and practices. It should be noted that the level of influence of each factor on CDT varies widely among terminals; nevertheless, the study does not attempt to measure this level. **Terminal characteristics & location** - Terminals can function as gateway ports serving the local and regional hinterland or as transshipment hubs between two regions. The terminal function is highly dependent on the port's geographic location. CDT patterns may vary depending on the terminal's function (Merckx, 2006).

Port policy & management - Port policy and management can have a direct impact on CDT. For example, the agreements between container terminals and shippers specify the allowable free time for CDT before demurrage fees are assessed. Terminal's hours of operation also depends on the terminal policy. Most terminals accept vessels 24 hours a day, but truck gates typically open Monday-Friday (occasionally Monday-Saturday) and cease operations at night.

Ocean carrier - An ocean carrier is a firm that owns or charters vessels to establish and operate liner shipping services (American Association of Port Authority, 2007). Ocean carriers often provide landside transportation services and may leave containers at the terminal for varying amounts of time. Also, because ocean carriers frequently own the containers, shippers are allowed different amounts of time to collect and return the containers.

Truck carrier – Truck carriers may have a contract either directly (with the consignor or consignee) or indirectly (with the freight forwarder or 3PL) to carry goods to the port or to a hinterland destination. The priority with which a container is picked up from or delivered to the port depends on the relationship with the client, ultimately impacting CDT.

Modal Split - The modal split of hinterland transportation can indirectly influence CDT. Merckx (2005) indicates that containers shipped by road have shorter dwell times, though container terminals linked by rail or barge services often provide faster distribution services for seaborne containers. **Container status** – The status of a container (full or empty) has an impact on CDT. The fees vary depending whether the container is full or empty. Additionally, although full containers typically have shorter CDT, the presence of empty container depots near the port can create minimal CDT for empty containers.

Content of a unit – The content of a container can impact CDT. Items such as perishable foods, hazardous cargo, and consumer electronics have different speeds with which they move through the supply chain.

Cargo flow pattern - The balance between imports and exports is not identical for all container terminals. Whether evenly split or favoring imports or exports, the distribution of cargo has an impact on CDT. It is often the case that import container CDT exceeds those of export containers.

Container's security level - Security and customs procedures at ports can impact CDT. Container checks based on factors such as port of origin or the shipper's C-TPAT status may cause delays or accelerate the release of the container. The evaluation of the impact of security on CDT remains incomplete as data is not available.

Business connection - The relationship between terminal operators and their customers (truckers and ocean carriers) might affect CDT. Terminals may implement priority systems based on long-term commercial or financial relationships with their clients (Rodrigue 2008). A carrier providing a larger volume for the terminal may have more influence on the terminal policy and might benefit from preferential rules, fees, and practices. For instance, a terminal may accept containers from particular carriers at any time period (late arriving or early dropping) affecting the overall CDT on the terminal.

Shipper – Shippers could be local or global firms, ranging from a minor to a major corporation. The shipments can be a routine procedure, a seasonal event, or a onetime occurrence. The shipper's characteristics, including its ability to hold the cargo as inventory, can determine when the container is picked up or brought to the terminal. **Consignee** - Consignees are the legal owners and ultimate recipients of the commodities shipped (Rodrigue, 2007). Consignees located in an urban area and close to a regional port may delay container pick up until they have available storage space, or because of high inventory expenses in the urban area. Just-In-Time (JIT) orders should not be expected to remain in a yard for a long period of time. In contrast, some consignees with low risk inventory policy and relatively low demurrage fees may use the storage yard as a safe and secure location for holding inventory.

Freight forwarder/broker - Freight forwarders are individuals or companies that prepare documentation and coordinate the movement and storage of cargo (American Association of Port Authorities access 2007). The efficiency of their operations can impact CDT. Improved coordination with ocean carriers and truckers for transportation of cargo may reduce CDT.

Third Party Logistics Company - 3rd party logistics companies (3PLs) are asset-based companies that offer logistics and supply chain management services to customers. Because the scheduling of container movements becomes the responsibility of the 3PL, CDT can be impacted by the company's practices.

Typically, the information on the above mentioned factors is being collected and is available through the terminals' data systems. Additional factors can also be defined influencing CDT which is not discussed here such as the application of the state of the art technology in containers handling, global economy, and security.

Figure 4-1 depicts the factors affecting the CDT and their interrelationships. The light blue shows CDT determinant factors resided and limited to a terminal boundaries, while the darker blue demonstrates factors resided outside of a terminal's boundaries.



Figure 4-1: The CDT determinants

4.3 Data Description and Specification

To investigate and model the correlation between CDT determinant factors and CDT, data from one of US container terminals was obtained. The data were provided by the terminal contain information for all containers that were handled by the terminal during a two- month peak period "Oct-November" (denoted as Period A in the Section 4-7), and a two-month non peak period, "January-February" (denoted as Period B in the Section 4-7). As illustrated in Figure 4-2, each container delivered by a truck, located in the inbound truck dataset, is linked by its container number and status to the corresponding record in the outbound vessel's data set. The established link will be employed to calculate the exact CDT.



Figure 4-2 : The link layout between truck and vessel datasets

For each container, the following information was available;

- Container ID,
- Ocean Carrier,
- Ocean carrier's assigned vessel,
- Trucker,
- Direction of movement (inbound/outbound),
- Operation day,
- Container's size (e.g. 20', 40')
- Container's type (e.g. dry, reefer),
- Container's status (empty, full), and
- Exact date and time of arrival and departure.

Because of the relatively limited modal share for rail and barge, the study excluded all non-truck container movements from the analysis. Transshipment containers and those that were temporarily offloaded from vessels (restowed) were also not included in the analysis. The preliminary statistical analyses are performed on dataset presented in the next chapter. The analysis of the historical data also revealed that more than 90% of import and export containers stay at the port for ten days or less. Hence, the loading of vessels is assumed to be related to the past 10 days of gate activities. Also, containers are assumed to depart the port within 10 days of their arrival.

The preliminary analysis on the data also revealed that the terminal has no significant transshipment volumes. Therefore, the export and import containers are transferred between the terminal and the hinterland via two major transportation modes: rail and road. Road transportation carries approximately 76 % of the export containers and 85% of the import containers. While the terminal is open 24/7 for vessel loading and unloading, the gates are open 16 hours a day (Monday through Friday 6:00 – 22:00) and 8 hours (8:00 – 16:00) on Saturday. The average export container's CDT is about 6 days and 4 days for import containers. The terminal has four days of a free time for export and import containers after that demurrage fees are calculated. In other word, containers stay free at the terminal for four days; though, they will be charged (demurrage fee), if they remain more than four days at the yard.

In the following, the characteristics of the observed data will be reviewed to probe proper techniques in mining data and establishing a relation between CDT and its determinant factors and CDT modeling.

4.4 CDT determinant factor characteristics

The investigation on the correlation between CDT determinant factors and CDT can be undertaken by analyzing data characteristics of the observed data. The assessment of determinant factors (attributes) revealed that most factors (e.g. container's status, Container's type, container's size, and operation day) have categorical, discrete and non numerical characteristics. With this specification, the dissertation explores a generic framework which can handle categorical data and model CDT based on information on determinants available through the terminals' data systems. For instance, container's status can have two possible values; full or empty; weekday can have six values. Container type and size have various combinations of size and type classes (e.g. dry and 40' containers). The CDT which is defined as the output attribute can be categorized and approached in two schemes; continuous (considering day and time of containers arrival and departure), and discrete (considering day of containers arrival and departure). In the correlation study and CDT modeling, CDT is defined in a daily base as it is in practices and classified in 10 possible values (0-9). This assumption is made to satisfy two requirements; 1) create homogenous dataset (categorical and discrete) to explore suitable data mining techniques; 2) enfold enough population in each CDT class, capable of deriving the relation between CDT determinant factors and CDT.

To capture the business connection between terminal operators and truck or ocean carriers, the following framework is developed considering the frequency of terminal visit by carriers (truckers) or containers volume handled by a specific carrier (ocean carrier).

4.4.1 Business Connection Characteristic

To capture the business connection in the form of categorical data, the dissertation develops an algorithm counting a number of containers handled (drop off / pick up) by each trucker or vessel in a particular time frame and assigns a class based on the

categorization algorithm. The algorithm defines "P" classes of truck or vessel based on a number of containers increasing by \mathcal{E} deterministically, as illustrated in the following figure.



Figure 4-3: the classification of truck and vessel

For instance, if a number of containers per each class is $300 (= \varepsilon)$ and a truck carrier has been found delivering 2500 export containers in the period of two months, as a maximum value for truck carriers, we will have 10 (=n) classes of truck carriers and this carrier is classified in the class number 10. Consequently, a carrier delivering 290 containers will be classified in Class I and a carrier delivering 1400 containers will be classified in Class V.

Using this defined threshold for each class, the following algorithm is created to assign each carrier to the associated class and model the "Business Connection" factor. The Excel macro written in VB is illustrated in appendix 1a & 1b.



Figure 4-4: The business connection algorithm for trucks or vessels classes

4.5 Data Mining Techniques

This section presents a description and evaluation of several techniques that can be used to mine data collected by terminal operators. The techniques, then, is utilized to establish the relationships between CDT and its determinants and CDT modeling (in the next section). To draw this relation and CDT modeling, the study evaluates some DM algorithms that are typically employed in mining databases. DM refers to the process of analyzing data in order to determine patterns and their relationships. Technically, data mining requires either exploring an immense amount of material, or intelligently probing it to find where the value resides. Three common approaches can be traced in mining data: 1) Market basket analysis, 2) unsupervised learning, and 3) supervised learning.



Figure 4-5: Hierarchy of data mining strategies (adapted from Roiger, et al., 2003)

The main purpose of **market basket** analysis is to find interesting relationships among retail products. The results of a market basket analysis help retailers design promotions, arrange shelf or catalog items and develop cross-marketing strategies. Associate rule algorithms are often used to apply a market basket analysis to a set of data (Roiger et al., 2003).

From a theoretical point of view, supervised and unsupervised learning differ only in the causal structure of the model. In unsupervised learning, all observations are assumed to be caused by a set latent variable. In this learning, each hierarchy needs to learn only one
step and therefore the learning time increases (approximately) linearly in the number of levels in the model hierarchy. Two very simple classic examples of unsupervised learning are clustering and dimensionality reduction (Valpola 2000). Unsupervised learningclustering determines whether relationships, in the form of notions, exist in the data. If a cluster finds such notions, then it can be deduced that a supervised model is likely to perform well, leading us to continue in the data mining process. In supervised learning, the model defines the effect of one set of observations, called inputs, has on another set of observations, called outputs. In other words, the inputs are assumed to be at the beginning and outputs at the end of the causal chain. The models can include mediating variables between the inputs and outputs. Supervised learning, which can be used for classification, estimation of continuous numerical data, and prediction of future behavior of data, is a more dominant mode of learning. As a subset of supervised learning, classification is probably the best implicit and applicable of all data mining strategies. In this method, the model builds a set of well defined classes with the capability of assigning a new instance to the set of classes (the dependent variable is categorical). The estimation process of supervised learning model determines a value for an unknown numeric output attribute with categorical concepts.

The prediction model, which forecasts future outcomes rather than current behavior, can have categorical or numeric output attribute. Many DM modeling tools generate models which provide prediction and informative description tasks (Roiger, et al., 2003).

Generally, the goals of prediction and description tasks are achieved by applying one of the primary DM methods. To choose an appropriate DM modeling technique, the dissertation has to examine how the objectives would be addressed by DM algorithm capabilities. The study also has to examine how the algorithm manipulates categorical, discrete and non-numeric data, as the most CDT determinant data has these characteristics.

This is a novel approach; since, to the best of the author's knowledge, this is the first attempt that DM algorithms are utilized to model CDT based on a set of determinant factors. The author strongly believes that DM algorithms can capture the hidden patterns between CDT and its influential factors (described above) as they demonstrate this capability (pattern recognition) in other applications clearly.

In the table below, DM problem types are related to appropriate modeling techniques following by the description of the most common modeling techniques. Each technique is reviewed concisely and the applicability of the algorithm in this study is investigated through an evaluation of the algorithm functionalities, and data characteristic supervised by the algorithm.

Table 4-1: DM problems with corresponding proposed DM algorithms (adopted from

Rider	Bos	kovic	Institute,	2001)
-------	-----	-------	------------	-------

Segmentation or clustering	K-Mean Clustering, Neural networks, Visualization methods
Dependency analysis	Correlation analysis, Naïve Bayesian, Association rules, Bayesian networks
Classification	Decision trees, Neural networks, K- nearest neighbors
Prediction	Regression analysis, Logistic Regression, Neural networks, K- nearest neighbors

4.5.1 K-Means clustering algorithm

Clustering generalizes micro data and organizes it into more homogeneous classes. Because clustering brings similar entities together, it partitions a data set into groups of similar points. One of the most popular techniques of clustering is K-Means algorithm or distance- based clustering. This algorithm assumes that all instances correspond to the points in the n-dimensional space Rⁿ. The nearest neighbors of an instance are defined in terms of the standard Euclidean distance.

To estimate the Euclidean distance, let an arbitrary instance *x* be described by the feature vector $\langle a_1(x),...,a_n(x) \rangle$, where $a_r(x)$ denotes the value of the rth attribute of instance *x*. Then the distance between two instances x_i and x_j is defined to be d (x_i, x_j) , where $d(x_i, x_j) \equiv \sqrt{\sum_{r=1}^n (a_r(x_i) - a_r(x_j))^2}$ Equation 4-1

In the nearest – neighbor learning, the target function may be either discrete valued or real valued (Mitchell 1997). The K-mean algorithm described next is a simple yet effective statistical clustering technique: (Lloyd 1982)

- 1. Choose a value for K, the total number of clusters to be determined.
- 2. Choose K instances (data points) within the dataset at random. These are the initial cluster centers.
- 3. Use simple Euclidean distance (using equation 4-1) to assign the remaining instances to their closest cluster center.
- 4. Use the instances in each cluster to calculate a new mean for each cluster.

5. If the new mean values are identical to the mean values of the previous iteration the process terminates. Otherwise, use the new means as cluster centers and repeat steps 3 through 5.

Though the K-means method is easy to understand and implement, *it has several major drawbacks making it an unsuitable tool in the classification of CDT determinant*

factors. The algorithm only works with real valued data. If we have categorical attributes such as some attributes in the CDT determinant factors, we must either discard them or convert the attributes' values to numerical equivalents. The K-means algorithm works best when the clusters that exist in the data are approximately the equal size. If an optimal solution is represented by clusters of unequal size, the K-means algorithm is not likely to find a best solution. As in our case, it is expected that the clustering procedure will not create the same size clusters; since CDT and its determinant factors demonstrate more populations on some classes than others such as more containers found in the CDT class of 0.

In addition, this algorithm is not capable of determining the significant CDT determinant factors in the formed clusters. Therefore, several irrelevant attributes can cause less than optimal results.

4.5.2 Logistic regression

As a prediction tool, logistic regression predicts a discrete outcome from a set of variables that may be continuous, discrete, dichotomous, or a mix of any of these. Consequently, logistic regression makes no assumption about the distribution of the independent variables. A dependent variable in logistic regression is usually dichotomous, that is, the dependent variable can take the value 1 with a probability of success P, or the value 0 with the probability of failure 1-P (Mitchell 1997). However, an application of logistic regression has also been extended to multinomial logistic regression where the dependent variable is more than two cases (0 and 1), as in our case, the dependent variable can have more than 10 values.

One approach to solve the multinomial logistic regression is converting the response (dependent variable) into a sequence of binary choices and develops a sequence of ordinary logistic models. By fitting these binomial logistic regression models separately, we can estimate the multinomial logistic regression model using the maximum likelihood of those models' results (Hastie et al., 2001).

The relationship between the predictor and response variables is not a linear function; the logistic regression function is used, which is the logit transformation of *P*:

$$P(x) = \frac{e^{(c+\beta_1x_1+\beta_2x_2+\dots+\beta_ix_i)}}{1+e^{(c+\beta_1x_1+\beta_2x_2+\dots+\beta_ix_i)}}$$
Equation 4-2

Where,

c = The constant of the equation or intercept of the regression model,

 β = The coefficient of the predictor variables, and

 $x_1...x_n$ = Independent attributes.

P = A probability of the prediction variable in the range 0 to 1.

An alternative form of the logistic regression equation is:

Logit
$$[p(x)] = \log \left[\frac{p(x)}{1-p(x)}\right] = c + \beta_1 x_1 + \beta_2 x_2 + \dots + \beta_i x_i$$
 Equation 4-3

The goal of logistic regression is to predict correctly the category of outcome for

individual cases using the most economical model. To accomplish this goal, a model is created that includes all predictor variables that are useful in predicting the response variable (Mitchell 1997).

Logistic Regression (LR) which is often deployed in document classification is capable of handling categorical data along a categorical multinomial output. However, LR is not widely used for data mining because of an assumption that LR is unsuitably slow for high-dimensional and large dataset. *The dissertation experienced this deficiency (slow convergence) in applying this model on the available dataset.*

4.5.3 Artificial Neural Network (ANN)

An Artificial Neural Network (ANN) is inspired by the ability of a human brain to solve, learn and think. The first attempt to model the brain was conducted by McCulloch and Pitts (1943). Since then, many attempts have been done to improve the model's drawbacks and shortcomings.

Basically, a nerve cell receives inputs from Dendrites. It performs some nonlinear analysis in the cell body and releases the decision or output from Axon. Therefore, three basic parts in the nerve cell, or **neuron**, are:

- Dendrites (inputs)
- Cell body
- Axon (output)

Accordingly, in an ANN, three basic layers have to be identified to create ANN topology; the input layer (as Dendrites), the hidden layer (as Cell body) and the output layer (as Axon). The input layer holds independent variables; the hidden layer contains hidden nodes which perform processes; the output layer contains dependent variables. Each input has an associated weight, which has been modified as the model is learning. In general, the ANN can be presented as:

$$\mathbf{y}_{\mathbf{i}} = f(\sum_{j} w_{ij} x_{j})$$
 Equation 4-4

Where,

 y_i = Output unit, w_{ij} = weight from unit j to unit i, x_j = Input unit, and f = Activation function, in the simplest form f can be a linear function (linear regression).

The weighted links also connect layers together. Two main architectures are developed for ANN: Feed forwarder and Radial basic network functions.

In the training of the ANN, the parameters are adjusted incrementally until the training data satisfies the desired mapping as well as possible. This is until \hat{y}_i matches the desired output y_i as closely as possible up to a maximum number of iterations. To perform this task, the weight of each unit has to be adjusted. This process requires that the neural network first computes the error derived from weighting. Then, outputs send back to the system for further adjustments. Before the performance of the ANN is evaluated, some parameters have to be identified. These parameters must be adequately set for an efficient performance of ANN. These parameters could refer to the number of hidden nodes, number of hidden layers, training and learning rule, momentum term, transfer function, cost function, weight initializing, and stop training.

In spite of wide spread usage of this technique, ANN is viewed as a black box with mystical relation between nodes. The study also experienced long processing time to explore a suitable topology for the outsized large database. *Hence, this study does not utilize this technique in CDT modeling.*

4.5.4 Naïve Bayes (NB) Algorithm

The NB algorithm is based on conditional probabilities. It uses Bayesian Theorem that calculates a probability by counting the frequency of values and combinations of values in the historical data. If "Y" represents the hypothesis (or dependent event) that we would like to examine and " α " represents the training data (or independent event) validating or invalidating the hypothesis, the theorem can be stated as follows.

Prob $(Y | \alpha) = [Prob (\alpha | Y) Prob(Y)] / Prob (\alpha)$ Equation 4-5

To calculate the probability of "*Y*" given " α ", the algorithm counts the number of cases where " α " and "*Y*" occur together and divides it by the number of cases where " α " occurs alone.

By stimulating from the Bayesian Theorem, NB calculates a probability by dividing the percentage of pair wise occurrences by the percentage of singleton occurrences (i.e. a set of one element). If these percentages are very small for a given predictor, they probably will not contribute to the effectiveness of the model (Roiger, et al., 2003). In mathematical form, assume target function $f: x \rightarrow Y$, where each instance x is described by attributes $\langle a_1, a_2, ..., a_n \rangle$. Most probable value of f(x) is: (Rider Boskovic Institute, 2001)



Naïve Bayes assumes that " α " attributes are x_i independent values

$$P(\alpha_1, \alpha_2, \dots \alpha_n \mid Y_j) = \prod_i P(\alpha_i \mid Y_j)$$
 Equation 4-7

which gives

Naïve Bayes classifier:
$$Y_{NB} = \frac{argmax}{Y_j \in Y} P(Y_j) \prod_i P(a_i | Y_j)$$
 Equation 4-8

Where,

 Y_{NB} = Most probable value Y= posterior probability $P(Y_j)$ = prior probability of Y_j $P(\alpha_i|Y_j)$ = likelihood of α_i given Y_j Or simply:

NB classifier= Highest Posterior Probability (Y_{NB}^{argmax}) = Prior probability $P(Y_j)$ * Likelihood of a_i given Y_j

The NB algorithm uses the relatively efficient, fast, and simplistic probability to discover the dependency between input attributes and each class of output attribute. In addition, this model can handle categorical and numeric data as input attributes and can be used for both binary and multiclass classification as an output attribute (Oracle Data Mining website), the suitable qualification for our dataset. NB classifiers need moderate to large training sets with independency in attributes. The most successful applications of NB algorithm include diagnosis and dependency analysis (Mitchell 1997). Considering NB data characteristics and its functionality, *the model presents its suitableness in the classification of CDT determinant factors*.

The NB algorithm is a highly scalable model building and scoring approach. Despite the assumption of independence, *we can argue that this dependency does not present a major concern in our dataset*, since this dependency is not distributed evenly in each class due to different effects of each determinant factor on CDT. In the worst case scenario, even we argue that the distribution of dependencies among attributes are evenly distributed in classes affecting the classification of NB, Zhang (2001) provided the proof that this dependency among attributes in a class might cancel each other out.

4.5.5 Decision tree Algorithms

Decision tree algorithms are powerful and popular tools for classification and prediction. The attractiveness of decision tree is due to the fact that decision tree represents *rules*. Rules can readily be expressed so that one can understand them or even directly used in database language. This method is able to handle both continuous and categorical variables (as in our case) and performs classification without requiring much computation. Decision tree learning is generally appropriate for modeling problems with the following characteristics (Mitchell 1997):

- Instances are represented by attribute- value pairs.
- Instances are described by a fixed set of attributes and their values.
- The target function has discrete output values.

- The training data may contain missing attribute values (the significance of this feature is critical in the CDT prediction, since we deliberately remove CDT values from some records to be defined by the developed model. More discussion will be presented in Section 4.7).

A weakness is that decision trees are less appropriate for estimation tasks where the goal is to predict the value of a continuous attribute. In addition, decision trees are prone to errors in classification problems with many classes and relatively small number of training examples.

A decision tree is a tree structured framework representing data with a top node (root of tree) describing different states of the output attribute. Data that offers the high information gain related to the output attribute is classified first and produces a series of splits or nodes. Each node of the tree denotes a class and the tree is split up until all states of the input attributes are covered in classes (Li et al., 2x006). Most algorithms that have been developed for learning decision trees employ a top-down, greedy search. The most popular greedy search algorithm is exemplified by the ID3 algorithm (see Figure 4-6 - Quinlan 1987) and its successor C4.5 (Quinlan 1993), utilized in this dissertation. C4.5 is a software extension of the basic ID3 algorithm to address some issues (e.g. pruning, handling missing value, improving computational efficiency) not dealt with in the basic ID3. The algorithm picks the best attribute and never reconsiders earlier choices for potential misclassification as described in the following:

Function ID3
Input: (R: a set of non-target attributes,
C: the target attribute,
β : a training set) returns a decision tree;
Begin
If β is empty, return a single node with value Failure;
If β consists of records all with the same value for the target attribute, return a single
leaf node with that value;
If R is empty, then return a single node with the value of the most frequent of the values of
the target attribute that are found in records of β ; [in that case there may be errors, examples
that will be improperly classified];
Let A be the attribute with largest Gain(A, β) among attributes in R;
Let $\{aj j=1,2,, m\}$ be the values of attribute A;
Let $\{\beta j \mid j=1,2,,m\}$ be the subsets of β consisting respectively of records with value a for
<i>A</i> ;
Return a tree with root labeled A and arcs labeled a1, a2,, am going respectively to the
trees (ID3(R -{ A }, C, β 1), ID3(R -{ A }, C, β 2),,ID3(R -{ A }, C, β m);
<i>Recursively apply</i> ID3 <i>to subsets</i> $\{\beta j j=1,2,, m\}$ <i>until they are empty</i>
End

Figure 4-6: ID3 decision tree algorithm

The focal point in developing the decision tree algorithm is the process of selecting attributes at each node. For the selection of the attribute with the most inhomogeneous class distribution, the algorithm employs the entropy perception. One interpretation of entropy from information theory is that it identifies the minimum number of bits of information required to encode the classification of an arbitrary member of β (i.e., a member of β drawn at random with the uniform probability). (Rider Boskovic Institute, 2001) If the target or dependent attribute takes on *c* different values, then the entropy of β relative to this *c*-wise classification is defined as

Entropy (β) = $\sum_{i=1}^{c} -P_i \log_2 P_i$ Equation 4-9

Where,

 p_i is the proportion of β belonging to class *i*.

Given entropy as a measure of the impurity in a collection of training examples, we can estimate the effectiveness of an attribute in classifying the training data, called information gain. The information gain of an attribute A relative to a collection of examples β is defined by (Mitchell, 1997)

Gain (
$$\beta$$
, A) = Entropy (β) - $\sum_{v \in Value(A)} \frac{|\beta_v|}{|\beta|} Entropy(\beta_v)$ Equation 4-10

The *Values* (*A*) is the set of all possible values for attribute *A*, and β_v is the subset of β for which attribute *A* has value *v* (i.e., $\beta_v = \{b \in \beta \mid A(b) = v\}$). The second term is the expected value of the entropy after β is partitioned using attribute *A*. The expected entropy described by this second term is simply the sum of the entropies of each subset β_v , weighted by the fraction of examples $|\beta_v|/|\beta|$ that belong to β_v . *Gain* (β , *A*) is therefore the expected reduction in entropy caused by knowing the value of attribute *A*(Mitchell, 1997). As depicted in Figure 4-6, the process of selecting a new attribute and partitioning the training examples is now repeated for each non-terminal descendant node until either of the following two conditions is met:

- every attribute has already been included in the tree structure, or
- the training examples associated with this leaf node all have the same target attribute value or their entropy is zero.

Using this process, decision trees clearly show which fields are most important for prediction or classification. *Considering the above mentioned features, decision tree learning also substantiates its capability in the CDT modeling.*

4.5.6 Hybrid Naïve Bayes and Decision Tree (NBTree)

The Naïve Bayesian tree learner, NBTree (Kohavi, 1996), combined naïve Bayesian classification and decision tree learning. After instances are classified using the C4.5 algorithm (ID3 successor) and a tree is grown, a naïve Bayes is constructed for each leaf using the data associated with that leaf, as described in the following procedure.

Input: A set T of labeled instances

Output: A decision tree with Naïve Bayes categorizers at the leaves.)
Begin

For each attribute Xi_ evaluate the utility, u(Xi) of a split on attribute Xi. For continuous attributes, a threshold is also found at this stage.
Let j = arg maxi(ui), i.e., the attribute with the highest utility.
If uj is not significantly better than the utility of the current node_ create a Naive_Bayes classifier for the current node and return.
Partition T according to the test on Xj. If Xj is continuous, a threshold split is used; if Xj is discrete, a multi_way split is made for all possible values.
For each child_ call the algorithm recursively on the portion of T that matches the test leading to the child.

Figure 4-7: the NBTree algorithm (extracted from Kohavi 1996)

As Kohavi stated in his algorithm, the NBTree algorithm is computing the utility of a node (Gain ratio described in the decision tree algorithm) by discretizing the data and computing the 5 fold cross-validation accuracy estimation using Naïve-Bayes at the node (Kohavi, 1996). NBtree seems to be a viable approach to generate classifiers, where:

- Interpretability of classifiers is the objective.
- Attributes are mostly relevant and dependent for classification.
- The dataset is large.

Because NBTree achieves higher accuracy than a naïve Bayesian classifier and decision tree learner in literature (Wang et al. 2006, Kohavi 1996, and Zhao et al. 2008), *this study also employs this algorithm as one of the candidates for the CDT modeling.*

4.5.7 Additional hybrid data mining algorithms

Other hybrid data mining algorithms have been developed to improve the efficiency of DM algorithms in some applications. Carvalho and Freitas (2004) proposed a hybrid decision tree/genetic algorithm method to cope with the problem of small disjunction in decision tree learning using the genetic algorithm. Wang (2006) proposed a hybrid algorithm that would combine the benefits of the pattern identification ability of the a priori DM algorithm (Associate rule) with the capability of GA operators. Zahidhassan and Verma (2007) combined k-means and Naïve Bayes with a neural network based classifier. The idea is to cluster all data in soft clusters using neural and statistical clustering and fuse them using serial and parallel fusion in conjunction with a neural classifier.

Anand(et al., 1998) proposed the hybridization of k-mean algorithm and neural network solutions that make it appropriate for use as a paradigm for addressing regression data mining goals. Castro and Murray (2000) adopted K-mean as the prototype of iterative model-based clustering with the Genetic algorithm, since they believe that this hybrid learning algorithm is more robust to noise and outliers. A review of these articles revealed that none of these algorithms is suitable for the work presented in this dissertation because of their applicability and data characteristics.

4.6 Methodology

This section presents a methodology and model formulation employed to estimate the container dwell time using a set of determinant factors defined in Section 3. Section 5 concluded that NB, DT, and NBTree are good candidates to model and estimate CDT. This section presents how these models can be formulated and executed on the available dataset (subsection 4.6.1 through 4.6.3). Upon the examination of these models, the model performance factors have to be determined and measured to select the robust model (subsection 4.6.4). The last subsection (4.6.5) presents the analytical relation between CDT and yard capacity, since the outcomes of the CDT modeling will be utilized in the three practical scenarios to estimate yard capacity and the terminal revenue earned from demurrage fee. The next section (4.7) applies this developed methodology on the observed data, after the exhaustive examinations of dependency analysis between available CDT determinent factors and CDT.

4.6. 1 Naïve Bayesian Modeling

To employ the NB model on the observed data, we assume that the independent variables (x) are factors influencing CDT (determinant factors) such that each one (x_i) is described by attributes $\{a_1..., a_n\}$. The dependent variable is the CDT (Y) with j (=10) classes based on the number of days containers stay in the yard. As explained in Section 4.4, the CDT is unitized daily, as it used in practice, compared with timely or half-daily to provide enough number of records in each class, suitable for further analytical analysis. For instance, one would like to determine the most probable dwell time value of empty (α_I) and full (α_2) export containers just arrived at the terminal. Based on Equation 4-8, we have;

 $\begin{cases} \text{posterior probability of } \alpha_1(=e) \text{ being } Y_{0,...,9} = \text{Prior probability of } Y_{0,...,9} * \text{likelihood of } \alpha_1 | Y_{0,...,9} \\ \text{posterior probability of } \alpha_2(=f) \text{ being } Y_{0,...,9} = \text{Prior probability of } Y_{0,...,9} * \text{likelihood of } \alpha_2 | Y_{0,...,9} \end{cases}$

Equation 4-11

Using the observed data, we have

Prior probability of $Y_{0,...,9}$ = Total population of $Y_{0,...,9}$ / Total number of records ; for instance, Prior probability of Y_0 = (2021/58149)=0.035

Likelihood of a₁ given $Y_{0,...,9} = (Number of containers a_1 = empty and have CDT =0,...9)/(number of containers have CDT =0,...,9); for instance, Likelihood of a₁ given <math>Y_0 = (Number of empty containers with CDT=0) / (Number of containers have CDT =0)$ **Likelihood of a**₂ given $Y_{0,...,9} = (Number of containers a_2 = full and have CDT =0)$ =0,...,9)/(number of containers have CDT =0,...,9); for instance, Likelihood of a₂ given $Y_0 = (Number of containers have CDT =0,...,9)/(number of containers have CDT =0,...,9);$ for instance, Likelihood of a₂ given $Y_0 = (Number of full containers with CDT=0) / (Number of containers have CDT =0)$

Table 4-2 demonstrates the results of the calculations on all value of Y. Derived from the above estimation, the empty export containers are most probably classified in CDT =2 (dwell time of 2 days) and full export containers are most probably classified in CDT=7 (dwell time of 7 days), as presented in bold in Table 4-2.

Table 4-2:	NB	model	estimation
------------	----	-------	------------

	Y0	Y1	Y2	Y3	Y4	Y5	Y6	Y7	Y8	Y9
Prior Probability of =										
Total population of										
Y0,,9/Total number of										
records)	0.035	0.096	0.11	0.11	0.13	0.13	0.13	0.13	0.08	0.05
likelihood of a1 given	0.65	0.73	0.64	0.52	0.44	0.3	0.3	0.28	0.3	0.33
likelihood of a2 given	0.35	0.27	0.36	0.48	0.57	0.62	0.7	0.72	0.71	0.68
Posterior Probability of a ₁										
being Y = prior probability										
of Y *likelihood of a ₁ given										
Y	0.023	0.07	0.072	0.056	0.058	0.05	0.04	0.036	0.023	0.017
Posterior Probability of a ₂										
being = prior probability										
of Y *likelihood of a2 given										
Y	0.012	0.026	0.041	0.052	0.075	0.079	0.092	0.093	0.054	0.036

The same estimations and analyses can also be performed to classify other CDT determinant factors in each class of CDT using the following algorithm for any CDT determinant factor with the value of $x_i = \alpha_1$.



Figure 4-8: The classification of CDT determinants using NB algorithm

4.6.2 Decision Tree (DT) Modeling

To employ DT model on the observed data, the first action is defining which CDT determinant factor has the most important value for prediction or classification among all input attributes (CDT determinant factors). The following process is deployed recursively for each attribute to choose the next one with the highest Gain value.

For instance, we are interested in determining from two CDT determinant factors (container status and container's day of arrival), which attribute is the best classifier and has the highest gain value. In *Gain* (β ,*D*), *D* is the day containers arrived at the port with n'=6 different categorized values; β_v is the subsets of β consisting respectively of all records in different class of CDT with value { $D_1 | d = 1...n'$ }. Given *N* records as training data sets described by containers arrival day (*D*) attribute and CDT as dependent variable with ten categorized class, we have

Entropy (
$$\beta$$
) = Entropy ($\eta_{(Dt0)}, \dots, \eta_{(Dt9)}$) = $-\sum_{i=Dt0}^{Dt9} \frac{(\eta_i)}{N} \log_2(\frac{(\eta_i)}{N})$ Equation 4-12

Entropy $(\beta_v) = -\sum_{i=Dt0}^{Dt9} \frac{N_{vi}}{N} \log_2 \frac{N_{vi}}{N}$ Gain $(\beta, D) =$ Entropy $(\beta) - \sum_{v \in (d_1, \dots, d_{n'})} \frac{|N_v|}{|N|} Entropy(\beta_v)$ Equation 4-13

Where,

N= Total records,

 N_v = number of records that have container arrival day of "v"

 N_{vi} = number of records that have CDT = "*i*" and container arrival day "v"

 $v = \text{Value}(D) = \{d1 \dots dn'\} = n' \text{ classified classes of container arrival day,}$

 $Dt_0....Dt_9$ = classified dwell time from D0 to D9 days,

d = Number of categorized classes for container arrival day at the terminal,

 $\beta = \{\eta_{(Dt0)}, \dots, \eta_{(Dt9)}\} = 10$ classes of CDT,

 $\beta_{vi} = \{ \eta d_{1(Dt0)}, \dots, \eta d_{1(Dt9)}, \eta d_{2(Dt0)}, \dots, \eta d_{2(Dt9)}, \dots, \eta d_{n'(Dt0)}, \dots, \eta d_{n'(Dt9)} \} = \text{subset of}$

 β with all CDT classes and possible value of container arrival day.

 η_i = Number of containers with CDT = *i*,

For container's status Gain (β ,S) has the same formulation with the exception that n' = 2and v= value of container's status. The estimation of gain value for these two determinant factors is shown in following:

	βv = Monday	βv=Tuesday	βv= Wednesday	βv = Thursday	βv = Friday	βv = Saturday
Entropy β_v	4.1	4.84	4.51	4.49	4.18	0.405
	i=DT ₀	i=DT ₁	i=DT ₂	i=DT ₃	i=DT ₄	i=DT₅
Entropy β	0.034*log ₂ 0.034	0.096*log ₂ 0.096	0.11*log ₂ 0.11	0.108*log ₂ 0.108	0.13*log ₂ 0.13	0.127*log ₂ 0.127
	i=DT ₆	i=DT ₇	i=DT ₈	i=DT₀	Sum	
Entropy β	0.13*log ₂ 0.13	0.129*log ₂ 0.129	0.076*log ₂ 0.076	$0.05*\log_2 0.05$	3.23	
	βv = Empty	βv = Full				
Entropy β_v	4.77	4.4				

Table 4-3: Decision tree outcomes derived from the observed data

For container arrival day

$$\begin{cases} \frac{N_{v}}{N} * Entropy (Bv = Saturday) = 0.0024\\ \frac{N_{v}}{N} * Entropy (Bv = Monday) = 0.62\\ \frac{N_{v}}{N} * Entropy (Bv = Tuesday) = 1.134\\ \frac{N_{v}}{N} * Entropy (Bv = Wednesday) = 0.98\\ \frac{N_{v}}{N} * Entropy (Bv = Thursday) = 0.94\\ \frac{N_{v}}{N} * Entropy (Bv = Friday) = 0.76 \end{cases} => Gain (\beta, D) = -1.21$$

For container Status

 $\begin{cases} \frac{N_v}{N} * Entropy (Bv = Empty) = 2.11 \\ \frac{N_v}{N} * Entropy (Bv = Full) = 2.45 \end{cases} => \text{Gain } (\beta, S) = -1.33 \end{cases}$

Gain $(\beta, D) > Gain (\beta, S)$; therefore weekday attribute compares to the container's status on the higher branch in tree structure.

The classifications of CDT determinants in each class of CDT will be performed by executing the above mentioned procedure for each attribute recursively and choosing the one on the main branches holding *the highest Gain value*.

4.6.3 NBTree Modeling

To deploy this algorithm in this application, Equations 4-12 and 4-13 are executed to form the tree structure; then the NB algorithm in Figure 4-8 is executed for each leaf estimating the probability of having the new instance in that class or particular leaf.

4.6.4 Validation and Measuring Model Performances

The above mention models are executed on the observed data in the next section. The results are compared against the observed data and validated using the cross validation procedure. 10-fold Cross-validation is used to validate the analyses results in each algorithm (model). K-fold cross-validation is the statistical method partitioning the data into K subsamples. A single subsample (K) is retained as the validation set for testing, while the remaining samples (K-1) are utilized as training data. The cross validation process is executed K times on K subsamples when each subsample is used exactly once as the validation sample. The K-results from K runs are averaged to create a single stratified cross validation estimation. The advantage of this method is that each instance is used once for testing and k-1 for training. Therefore, the performance of model is tested and validated k-time with the datasets which have not seen and examined before. The results of these examinations are presented in the subsection 4.7.3.

The outcomes of the cross validation procedure are utilized to measure the model performance factors. The assessment of the model performance factors are, then,

contributed to the selection of the most robust model. Afterward, the selected model is deployed to estimate CDT and utilized in the final analysis –Estimation of terminal yard capacity and revenue using CDT. To measure the overall model performance and choose the appropriate model, four factors are considered:

- Correctly classified instances,
- Kappa statistic,
- Root mean squared error, and
- Processing time.

The Root Mean-Squared Error (RMSE) is computed by taking the root average of the squared differences between each predicted (computed) value and its corresponding origin value, as depicted in the following equation.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} (y - y')_{i}^{2}}{n}}$$
Equation 4-14

Where,

- y = Actual variable,
- y' = Estimated variable,
- n =total number of records.

This evaluation method, which is one of the most commonly used measures of success for quantitative data, would not be an efficient and sufficient factor in categorical data. As the correlation coefficient measures the statistical correlation between the predicted and actual values for numeric data, Kappa statistic or Kappa coefficient is used as a means of classifying agreement in categorical data, which measures the agreement of predictions with the actual class. Kappa can be

$$Kappa = (O - C) / (1 - C)$$
Equation 4-15

Where,

O = Observed agreement = Observed- corrected proportional agreement between actual and predicted classified records,

C = Chance agreement = Chance-corrected proportional agreement between actual classified records and the predicted classified records.

$$C = \sum_{i=1}^{m} n_{oi} * n_{ci}$$
 Equation 4-16

Where,

 n_{oi} = The chance (or probability) of having the observed value of *i*, n_{ci} = The chance (or probability) of having the predicted value classified in the same class of observed value of *i*.

A kappa coefficient of 1 means a statistically perfect model; 0 means that every model value is different from the actual value and what would be expected by chance; and a negative value (-1 in maximum) indicates agreement less than chance showing potential systematic disagreement between the observers. A kappa statistic of 0.7 or higher is generally regarded as a good statistic correlation, but of course, the higher the value, the better the correlation.

The correctly classified instance is the average of the number of instances classified correctly in each class of the CDT for the test data set in 10 folds. The reported

processing time is the time to build the models without cross validation test time. The processing time in this study is the time to build the models under present condition (Windows VISTA, 2GB RAM, 2GHZ) without cross validation test time.

4.6.5 Analytical Relation between CDT and Yard Capacity

The analytical CDT modeling technique developed above assists the author to create some practical scenarios. In these scenarios, the terminal yard capacity and the terminal revenue earned from the demurrage fee are calculated using the estimated CDT. To execute these scenarios, the analytical relation between CDT and yard capacity has to be studied and determined. In the following, some studies that investigate and provide this analytical relation are reviewed.

Hoffman (1985) developed the following equation to estimate the storage yard area using the CDT meeting the expected demands,

$$CY = (C*A*T)*(1+F)/360$$
 Equation 4-17

Where,

CY =Container yard area (m²),

C = Expected container volume (TEU),

 $A = Area (m^2) per container TEU,$

T =Average CDT, and

F = Peaking factor (about 20%) ensuring the storage space sufficiency.

As explained in Chapter three, Dally (1983) developed the following equation to estimate the number of containers accommodated in a container yard or the annual yard capacity C(TEUs/Yr) using the CDT to meet the existing supply.

$$C = (C_s *H*W*K') / (T*F)$$
 Equation 4-18

Where,

 C_s = Number of container ground slots (TEU),

H = Mean profile height ($C_s *H$ = static capacity of the container storage yard),

W = Working slots (TEUs) in the container storage expressed as a proportion (0.8 -

0.9),

K' = Number of days per year (365),

T = Mean CDT in the *CY*, and

F = Peaking factor (about 20%) ensuring the storage space sufficiency.

The dissertation utilizes equation 4-18 to calculate the storage yard capacity dedicated to import and export containers based on the CDT.

4.7 Case Study

This section provides the examination of the methodology developed above on the observed data. The following subsection assesses the aptness of the theorem that the CDT determinant factors affects the container dwell time. Subsections 4.7.2 and 4.7.3 present the results of the deployment of the DM algorithms on the observed data and reveal the robust selected model. Finally, the application of this modeling technique is explored on the three practical scenarios estimating the terminal yard capacity and the terminal revenue through the CDT estimation.

4.7.1 Dependency Examination

As a first step, and to confirm our proposition that determinant factors defined and described in the section 4.2 affect the CDT, the significant percentage values of some CDT determinant factors in each class of CDT are extracted from more than 200,000 records of import and export containers during the limited time period. Appendix 2a illustrates one of the attribute profile tables employed on export containers. In each finding, the study attempts to interpret the results by probing the interrelation between other CDT determinant factors and the outcomes. It should be noted that the importance of each of these factors on CDT and the ability of terminal operators to influence them varies widely among terminals.

Analysis 1: Impacts of Container's status (Full or Empty)

One of the proposed determinant factors is the container's status (empty or full). Since nearly 99% of the import containers were classified as full (as opposed to about 56% of export containers), the analysis was confined to exports.Table 4-4 shows that about 50% (in period A) and 45% (in period B) of empty export containers are distributed in the CDT class of two or less (class of 0, 1, and 2). This table shows the distribution of container's status (full and empty) for two periods of A and B (first column) in different classes of CDTs (column two through 11).

Table 4-4 : Distribution of loaded (full) and	d empty containers in different CDT classes
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Container's status		CDT								
	0	1	2	3	4	5	6	7	8	9
FULL(Period A)	3.3%	4.1%	6.7%	8.9%	11.1%	12.4%	13.2%	14.1%	14.8%	11.3%
EMPTY(Period A)	17.8%	16.9%	13.9%	11.3%	8.7%	7.2%	6.3%	5.2%	4.3%	8.5%
FULL(Period B)	6.4%	4.9%	6.6%	8.8%	10.4%	11.4%	12.8%	13.2%	13.0%	12.5%
EMPTY(Period B)	14.3%	16.1%	14.1%	11.5%	9.5%	8.4%	6.6%	6.2%	6.4%	7.0%

More investigation is also performed on the percentage of having empty or full containers in each class of CDT. As illustrated in Figure 4-9, one can conclude that full export containers can mostly be expected to stay in the yard for three days or more; while empty containers stay at the yard for three days or less. While, Table 4-4 demonstrates how the total number of full or empty export and import containers are distributed in different classes of CDT; Figure 4-9 depicts how the total number of containers in each class of CDT is dispersed into two statuses (empty and full).



Figure 4-9: Distribution of loaded (full) and empty containers in each CDT class

One interpretation behind the low CDT value of empty containers could be the existence of an empty depot at or near this terminal. Commonly, empty containers stay at the empty depot until they are brought to the terminal to be loaded on their carrier's vessel. In this terminal, the free time for export containers was four days after that demurrage fees were calculated. Hence, empty containers left the empty depot and arrived at the terminal four days or less before the vessel's arrival. As it can be observed from the subsequent sections, the container's status plays a major role in the duration that containers stay in the yard.

Analysis 2: Impacts of Ocean Carriers

The next analysis considered whether containers transported by certain ocean carriers were more likely to have certain dwell times. Figure 4-10 illustrates the containers profile transferred by these two Ocean carriers considering CDT. As depicted in Figure 4-10, Ocean carrier C has a greater percentage of lower value CDT classes for export containers. Alternatively, Ocean Carrier D embarked containers with the higher value of the CDT.



Figure 4-10: Distribution of CDT for two ocean carriers

To interpret these events, other CDT determinant factors for these ocean carriers are studied and shown in Table 4-5. This table depicts the related determinant factors including status (shown in column three), three categories of CDT (category 1 = CDT of 0, 1, 2, 3 days shown in column six; category 2 = CDT of 4, 5, 6 days shown in column five; category 3 = CDT of 7, 8, 9 days shown in column four), and truck class (shown in

column seven) associated with two ocean carriers (shown in column two) for two periods (shown in column one). Ocean Carrier C, which has frequent terminal visits (about 10% of all import and export containers), imports dry and full containers. More than 70% of its export containers are empty and dry. Empty containers hauled by this carrier contribute to more than 50% of the export volumes which have the CDT of three or less (as highlighted in Table 4-5). This finding demonstrates that this ocean carrier dedicates its vessels on back trips to haul empty containers.

Meanwhile, Ocean Carrier D, taking about 20% of total import and export containers throughout the terminal, delivers more than 96% dry and 100% full containers on import and transports less than 35% of empty containers on export(row 1 and 2 in column 3). As shown in the Table 4-5, this ocean carrier loads containers that stayed at the terminal more than 7 days (i.e. CDT of 7, 8, and 9), as highlighted in this table. For import containers, no significant events are experienced by this ocean carrier. Based on the preceding results, ocean carrier D provides relatively more productive trips than ocean carrier C since it carries full import containers and embarks a considerable amount of full export containers. By considering that this ocean carrier is one of major ocean carriers in the terminal (20% of whole containers volume), an uncommon behavior can affect the terminal CDT value drastically. Therefore, one can conclude that an increase in full export containers boarded by this ocean carrier can extend the average CDT at the terminal.

As illustrated in the last column of Table 4-5, both ocean carriers were on contracts with truck carriers that visited the terminal frequently. Truck class of 4, 5, and 6 demonstrates that export containers are drayed by truckers carrying 100 to 1000 containers per two

months period. As noted before, truck class defines the volume of containers drayed by a particular truck carrier. Therefore, one can conclude that any changes in these ocean carriers' behaviors can affect the truck gates too.

Export	Ocean Carrier	status (Empty)	CDT(7,8,9)	CDT(4,5,6)	CDT (0,1,2,3)	Truck class (4,5,6)
Period A	Ocean carrier D	35%	35%	30%	35%	61%
Period B	Ocean carrier D	33%	34%	39%	26%	63%
Period A	Ocean carrier C	76%	12%	33%	55%	68%
Period B	Ocean carrier C	71%	17%	31%	52%	68%
			Import			
Period A	Ocean carrier D	0	8%	37%	56%	64%
Period B	Ocean carrier D	0	6%	33%	61%	66%
Period A	Ocean carrier C	0	4%	29%	67%	71%
Period B	Ocean carrier C	0	3%	36%	61%	73%

Table 4-5: Ocean carriers and their related determinant factors

Analysis 3: Impacts of Truck Carriers

To examine whether some truck carriers follow a particular pattern to dray their containers, two truck carriers contributing significantly in some classes of CDT are chosen.

To determine how containers of these truck carriers are distributed in ten classes of CDT, the percentage of this dispersion is investigated and summarized in Table 4-6. This table depicts the related determinant factors including status (shown in column four), three categories of CDT (category 1 = CDT of 0, 1, 2, 3 days shown in column eight; category 2 = CDT of 4, 5, 6 days shown in column seven; category 3 = CDT of 7, 8, 9 days shown in column six), and container's type (shown in column five) associated with two truck carriers (shown in column two) draying certain counted containers (shown in column three) in two periods (shown in column one). For Carrier K, import containers were 100% full and debarked by three major ocean carriers. This carrier carried around 1500

containers per month⁷. Although the average CDT for import containers was 4 days, more than 30% of import container volumes drayed by this truck company had a CDT of 7 to 9 days (highlighted cell in Table 4-6). It is worth to mention that most truck carriers had a higher rate of drayage in the first four days and decreased significantly on the 7th to 9th days. Given that Truck carrier K is a large carrier, we can claim that longer CDT could affect the yard terminal capacity and truck gates considerably. As illustrated in Table 4-6, this truck company delivered 100% empty containers (full = 0%) with less volume in export procedure (the export volume is about 1/3rd of import volume) which embarked majorly by three ocean carriers (more than 65%). As explained before, empty containers had shorter dwell time which can be confirmed here, as well (CDT (0, 1, 2, 3) = 64%).

Simultaneously, Truck Company Z, which dropped off full and dry containers (100%) at the terminal, had longer CDT than the average. For this company, the CDT of 7, 8, and 9 contributed to over 56% to 75% of the whole volume. Containers dropped off by this trucker were embarked onto vessels owned by three major ocean carriers (i.e. more than 72%). This company was classified in a truck class which drayed more than 500 to 700 containers in the period of two months. This company had an insignificant volume of import containers. It seems this truck carrier, which hauled mostly export containers, worked for consignees which preferred to pay demurrage fee than inventory fee. This claim can be made since demurrage fees are assigned to containers remaining in the terminal more than four days. It is important to consider that, the average CDT of export containers was 6 days.

⁷ Trucker K was classified in the truck class 13 which carried more than 3000 containers during two months period.

Import	Trucker	population	status (Full)	Container type (Dry)	DT (7,8,9)	DT (4,5,6)	DT (0,1,2,3)
Period A	Company K	2402	100%	100%	33%	28%	39%
Period B	Company K	2700	100%	100%	32%	25%	43%
Period A	Company Z	44	100%	41%	9%	32%	59%
Period B	Company Z	18	100%	94%	0%	11%	89%
			Export				
Period A	Company K	869	0%	100%	16%	20%	64%
Period B	Company K	728	0%	100%	22%	40%	38%
Period A	Company Z	703	100%	100%	75%	23%	2%
Period B	Company Z	555	100%	100%	56%	43%	2%

Table 4-6: Truck carrier and their related determinant factors

Analysis 4: Impacts of Content of a Unit – <u>Container's Type and Size</u>

To examine whether a container's type and size might have any effect on the CDT, dry and reefer containers data were compared in each class of CDT (Figure 4-11). As it appears in this figureFigure 4-11, no specific pattern could be found between different classes of CDT for dry import and export containers. Most of them contributed an almost equal share (i.e. between 7 to 13 percent) in different classes of the CDT. Meanwhile, reefer containers mostly leave the terminal during the first three days. It is worth to mention that refrigerated containers had two days free time providing a possible explanation of this pattern.



Figure 4-11: Distribution of containers type and size in each CDT class More investigation is performed to determine how the container types and sizes are distributed in ten classes of CDTs and the results are summarized in Table 4-7. This table depicts the related determinant factors including status (shown in column three), two categories of CDT (category 1 = CDT of 0, 1, 2 days shown in column four; category 2 = CDT of 3, 4, 5 days shown in column five), and truck carriers (shown in column six) associated with the container's type and size (shown in column two) for two periods (shown in column one).

As illustrated in this table, most 20' reefer export containers were full (highlighted rows), in contrast with other type of containers (40'reefer and dry). This characteristic was found for both periods. For these containers, more than 70% of them were shipped within the first three days (row two and five; column four), though the CDT increased significantly for other type of containers and sizes. The investigation on truck class of

truck carriers draying 20' reefer containers showed that they are in classes of four to seven.⁸

Meanwhile, 20' reefer import containers were empty more than 56% for period A (or 44% full-highlighted row) and 65% for period B(or 35% full – highlighted row) – in stark contrast with other container types and sizes (dry and 40' reefer containers). These findings can educate the port operator that a particular container's type and size (i.e. 20' reefer containers) perform different behaviors and have different effects on the CDT. Although 20' reefer containers might contribute to small portion of total volume carried by these carriers, the special treatment of reefer containers (i.e. perishable products) might obligate truckers to postpone their services on other shipments.

Export	Container type and size	Status=Full	CDT (0,1,2)	CDT (3,4,5)	Trucker(4,5,6,7)
Period A	20' reefer	72%	73%	13%	89%
Period A	40' reefer	24%	27%	41%	71%
Period A	40' dry	55%	27%	37%	68%
Period B	20' reefer	82%	80%	12%	85%
Period B	40' reefer	23%	30%	36%	73%
Period B	40' dry	56%	22%	37%	75%
Import	Container type and size	Status=Full	CDT (0,1,2)	CDT (3,4,5)	Trucker(4,5,6,7)
Import Period A	Container type and size 20' reefer	Status=Full 44%	CDT (0,1,2) 50%	CDT (3,4,5) 44%	Trucker(4,5,6,7) 52%
Import Period A Period A	Container type and size 20' reefer 40' reefer	Status=Full 44% 100%	CDT (0,1,2) 50% 72%	CDT (3,4,5) 44% 25%	Trucker(4,5,6,7) 52% 83%
Import Period A Period A Period A	Container type and size 20' reefer 40' reefer 40' dry	Status=Full 44% 100% 100%	CDT (0,1,2) 50% 72% 49%	CDT (3,4,5) 44% 25% 38%	Trucker(4,5,6,7) 52% 83% 73%
ImportPeriod APeriod APeriod APeriod B	Container type and size 20' reefer 40' reefer 40' dry 20' reefer	Status=Full 44% 100% 100% 35%	CDT (0,1,2) 50% 72% 49% 41%	CDT (3,4,5) 44% 25% 38% 43%	Trucker(4,5,6,7) 52% 83% 73% 84%
ImportPeriod APeriod APeriod BPeriod B	Container type and size 20' reefer 40' reefer 40' dry 20' reefer 40' reefer	Status=Full 44% 100% 100% 35% 100%	CDT (0,1,2) 50% 72% 49% 41% 73%	CDT (3,4,5) 44% 25% 38% 43% 24%	Trucker(4,5,6,7) 52% 83% 73% 84% 73%

Table 4-7: Container's Type and Size and their related determinant factors

⁸ Trucker carried 100 to 1200 containers per two months period.
Analysis 5: Impact of Port policy-<u>Daily Terminal Operation</u>

Figure 4-12 presents the distribution of daily activities in each CDT class. As illustrated in this figure, export containers which were left on Friday had a CDT of zero with the percentage value of 40% (defined by the star sign in the Figure 4-12). This percentage value was higher than the rest of the percentage values in this class that occurred on other days. This characteristic could be observed for both periods.



Figure 4-12: Distribution of daily activities in each CDT class

To provide the reasoning for the correlation between Friday and shorter dwell time, more examinations were performed to discover how the weekdays' container activities, considering container status, are distributed in ten classes of CDTs. The results are summarized in Table 4-8. This table depicts the factors considered for this analysis including status (shown in column four), the value of two CDT categories (category 1 = CDT of 0, 1, 2 days ; category 2 = CDT of 7, 8, 9 days shown in column three), the percentage of container's population (shown in column two), reefer/heater containers

(shown in column five), and the weekday containers out by vessel for export containers (shown in two weekday categories in column six and seven) for two periods (shown in column one).

As illustrated in this table, the shorter CDT (i.e. two days or less), which contributed to more than 24% of the whole container volume (row2 and 4; column two), had more than 70% of empty containers (column four; highlighted cell). These containers were shipped out by vessel on Friday, Saturday, and Sunday with the percentage of 50% (column six; highlighted cell). Meanwhile, containers with longer CDT values (i.e. 7 days or more) which were full with the percentage of 75% (or 25% of empty= column two, row three), mostly left the terminal on Wednesday and Thursday with the percentage of about 50%. This pattern could be observed for both periods of A and B. The integration of the previous and present results allows for the conclusion that empty containers mostly arrived at the terminal from the empty depot on Friday to be shipped out in the next day or two. One of potential benefits derived from this analysis would be the establishment of a new policy at the terminal such as a dedication of specific lanes at truck gates to handle empty containers more efficiently and promptly on Friday.

For import containers, no specific patterns could be found between the percentage of weekday and CDT classes. As expected, import containers had shorter dwell time.

Export	Percentage of population	CDT	Status (Empty)	Reefer & heater	Out By Vessel = Fri, Sat, Sun	Out By Vessel = Wed, Thu
Period A	28%	0,1,2	73	5%	50%	
	25%	7,8,9	25	3%	34%	46%
Period B	24%	0,1,2	67	8%	57%	
	26%	7,8,9	29	3%	28%	52%

Table 4-8: Daily terminal operation and their related factors

4.7.2 CDT Estimation and DM Algorithm Deployment

Based on the earlier data analyses, three DM learning algorithms are deployed on 11,000 records of export and import containers extracted from the actual data: Decision tree, Naïve Bayes, and NBTree. The first objective in this deployment is examining the robustness of each algorithm in classification and estimation. The models can estimate CDT based on the classification of CDT determinant factors in each class of CDT. Each instance (record) contains the following attributes (CDT determinant factors) as input variables. The CDT is considered as the output attribute.

- Classified container status,
- Classified trucker,
- Classified vessel carrier,
- Classified container's size & type,
- Classified weekday container in,
- Classified weekday container out,
- Classified truck class, and
- Classified vessel class.

The WEKA software application, which is a collection of machine learning algorithms for data mining tasks, is utilized to implement the algorithms on the sample data. The sample of decision tree deployment on the obtained data in the WEKA software is illustrated in Appendix 2b.

4.7.3 Model Selection

Table 4-9 demonstrates the outcomes of three DM modeling techniques implemented on a subsample of one run in cross validation process. As depicted in Table 4-9, NBtree and

Decision Tree technique predict the CDT more accurately than NB. The addition sign "+" in some records notes instances when the actual data and DM techniques results are different. For instance, decision Tree and NBtree contained 4 and 5 incorrectly classified instances, respectively. NB, however, contained 12 instances that were incorrectly classified.

		Dwell time (Day)						
				Predicted_Decision				
Instance	Actual	Predicted_NB	Predicted_NBTree	Tree				
460	3	5+	3	4+				
461	3	5+	3	3				
462	3	4+	3	3				
463	3	3	3	3				
464	3	7+	3	3				
465	3	3	3	3				
466	3	5+	3	3				
467	2	0+	2	2				
468	2	5+	3+	3+				
469	2	5+	3+	3+				
470	2	1+	2	2				
471	2	1+	2	2				
472	2	0+	4+	3+				
473	2	1+	2	2				
474	2	2	1+	2				
475	2	2	2	2				
476	2	2	2	2				
477	2	2	1+	2				
478	2	2	2	2				
479	2	2	2	2				

Table 4-9: The result of deployment of three DM algorithms on one subsample

To measure the overall DM algorithm performance, the study is calculated the value of four model performance factors defined in the above section (subsection 4.6.4). In this evaluation, the study is effectively trying to compare the same sample sets in each scheme together and average the factors out at the end.

Table 4-10 presents the outcomes of this examination derived from the execution of the models on four different samples with 11000 instances (record) in each dataset randomly selected from import and export container databases.

The results demonstrate that NB presents less efficient results than two other techniques. As shown in Table 4-10 (third column) and Table 4-9 (third column), NB depicts its shortcomings in classifying the instances efficiently in each class of CDT. Fourth column (Kappa Statics) also provides more evidences that NB has underperformed comparing with NBtree and decision tree techniques. On the other hand, the decision tree and NB tree, both, provide acceptable and robust statistical results; however, the model creation time including processing time (noted in Table 4-10) and cross validation test time (adds another 15 minutes) for decision tree is much less.

Therefore, the decision tree model is selected as the suitable modeling technique for the CDT prediction utilized in the next section.

	Data	Correctly	Kanna	Root mean	
Model	Sample	instances	statistic	error	processing time
Decision Tree (C4.5)	Export	0.74	0.71	0.19	0.84 seconds
NBTree	Export	0.73	0.7	0.21	90.85 seconds
Naïve Bayes	Export	0.3	0.22	0.29	0.03 seconds
Decision Tree (C4.5)	Export	0.82	0.8	0.16	0.81 seconds
NBTree	Export	0.84	0.82	0.17	87.45 seconds
Naïve Bayes	Export	0.35	0.27	0.29	0.04 seconds
Decision Tree (C4.5)	Import	0.83	0.8	0.16	0.7 seconds
NBTree	Import	0.83	0.81	0.17	84.31 seconds
Naïve Bayes	Import	0.40	0.31	0.28	0.15 seconds
Decision Tree (C4.5)	Import	0.82	0.79	0.16	0.42 seconds
NBTree	Import	0.82	0.79	0.17	79.91 seconds
Naïve Bayes	Import	0.41	0.31	0.28	0.02 seconds

Table 4-10: The outcomes of the DM Models on 11000 instances

4.7.4 Application development of the selected model

As stated earlier, CDT modeling based on its determinant factors may assist in achieving a desired balance between suitable CDT and an adequate yard capacity. In this subsection, we utilize the decision tree technique to estimate the dwell time in different scenarios when containers status, truck gate schedules, or ocean carriers are changed. Finally, the dissertation evaluates the impact of the new CDT estimated by decision tree on the terminal storage yard capacity and the terminal earnings with the collection of additional demurrage fees. This subsection attempts to demonstrate how the results of this study can be merely incorporated with the practical estimation executed routinely in terminals (Equation 4-17 and 4-18).

The container's status is selected, since the calculation of posterior probability presented in Table 4-2 demonstrated that full containers are more likely to have longer dwell time than empty containers because empty container depots are available near-by the terminal under consideration. Truck gate schedules indicate the effect of "day of the week" attributes on CDT as probed in the preceding section. Similar calculations are also performed on ocean carriers, which depict that some ocean carriers have high posterior probability in lower classes of CDT and some contribute more on higher classes of CDT.

Terminal yard capacity and revenue estimation based on variation in CDT

In the following scenarios, we considered that the static capacity of the storage yard for import and export containers is about 1,000 TEU for each category (yard zone dedicated to import and export containers). The values of three determinant factors (i.e. container status, truck gate hours of operation, and ocean carrier) were changed for import and export containers in the dataset. The CDT of those records was left blank to be estimated using decision tree. The CDT of each scenario is calculated by averaging out the CDT of 1100 records in 10-folds.

Although the increase of CDT reduces yard capacity (Merckx 2005), increases unproductive re-handling moves (Huynh 2008), impedes the loading of ocean vessels and trucks, and increases labor costs and maintenance fees, it may serve as a revenue stream for terminal operators who charge demurrage fees. In the following analysis, the dissertation assesses the tradeoff between storage yard capacity and earnings from demurrage fees. This analysis could assist terminal operators in determining how to better achieve a desired balance between CDT and yard capacity. Additional research that goes beyond the capacity-revenue tradeoff is necessary to more thoroughly assess the impact of reducing CDT.

To calculate the demurrage fee, we consider that the terminal has four days of free time for empty and full containers. After these four days, a demurrage fee is charged for each extra day (values are according to $(FMI)^9$:

1-4 extra days \$45.00 per day,
5 - 9 extra days \$95.00 per day, and
10 days and above \$245.00 per day

Considering all of the above-mentioned assumptions and calculations, a base case scenario is developed for import and export containers and outcomes are presented in Table 4-11. It appears that the import containers have less CDT (i.e. 2.89 days) than

⁹ FMI International, NY/NJ Terminals Cut Free Time Raise Demurrage, March 28 2005, <u>http://www.summitgl.com/eflash/Issue002.html</u>, viewed July 2009.

export containers (i.e. 4.3 days). The annual yard capacity for dedicated import and export containers is estimated using Equation 4-18; therefore, we have:

Annual yard capacity for export=c = (1000*0.85*365)/(4.3*1.2) = 60125.97

Annual yard capacity for import=c = (1000*0.85*365)/(2.89*1.2) = 89460.78Revenue from demurrage fees is calculated based on the actual or estimated (for each scenario) CDT and according to the cost structure presented above. It is assumed that the demand is not sensitive to the fee (i.e., the demand is fixed).

		Annual Yard	Change in		
	Average	Capacity	capacity		Change in
G	CDT (Dara)	(TEU per	(TEU per	Demurrage fee	Revenue (\$
Scenarios Pasa gamaria for	(Day)	annum)	annum)	(\$ per annum)	per annum)
Export	4.3	60.125.97	0	\$ 138.246.00	\$ 0
Base scenario for		00,120197	•	¢ 100 <u>,</u> 21000	÷ ·
Import	2.89	89,460.78	0	\$ 50,262.70	\$ 0-
Scenario 1: Changing empty export containers to full	4.53	57,073.22	-3,052.75	\$ 143,297.20	\$ 5,051.20
Scenario 1: Changing empty import containers to full	2.93	88,239.48	-1,221.30	\$ 53,294.80	\$ 3,032.10
Scenaio2: Closing Saturday activity at truck gates (for Export)	4.39	58,898.92	-1,227.05	\$ 141,845.20	\$ 3,599.20
Scenaio2: Closing Saturday activity at truck gates (for Import)	2.98	88,068.15	-1,392.63	\$ 53,076.40	\$ 2,813.70
Scenario3: Exchanging container volumes between two ocean carriers (Export)	4.37	59,162.85	-963.12	\$ 140,387.00	\$ 2,141.00
Scenario3: Exchanging container volumes between two ocean carriers (Import)	2.92	88,541.67	-919.11	\$ 51,789.00	\$ 1,526.30

Table 4-11: Summary of finding for base case and different scenarios

Scenario 1: Changing the status of containers from empty to full

This scenario assesses whether a change in terminal characteristics has an impact on the CDT, container yard capacity, and demurrage fees. By changing the status of containers (import & export) from empty to full, the decision tree outcomes show that the average CDT increases slightly and the annual yard capacity is reduced by about 3000 TEU per annum for exports and about 1000 TEU per annum for imports; demurrage fees increase by about \$5,000 for export containers and about \$3000 for import containers. It is worth to mention that, the sample data indicated that nearly 99% of import containers were full as opposed to about 58% of export containers.

Terminal operators may prefer to earn more from the demurrage fees when yard capacity is not a significant constraint. Alternatively, the operator could attempt to decrease the dwell time by increasing demurrage fees or shortening the free time in order to gain more storage yard capacity during peak season.

Scenario 2: Closing truck gates in low volume conditions

The data set includes information on containers that arrived at or departed from the terminal by truck on a Saturday. Most container terminals, however, do not open their truck gates on Saturdays. This scenario investigates the impact of a Saturday truck gate closure on the yard capacity and terminal revenue. Although this scenario was applied only to a small portion of the observed volume (1/70th), it still shows that ceasing Saturday truck operations merits consideration, as it increase revenues, although it reduces capacity. A more elaborate economic analysis may require to perform further evaluation on the effectiveness of this policy.

Scenario 3: Changing ocean carrier

This scenario examines changes in circumstances when an ocean carrier diverts its business to another terminal, while the volume of another ocean carrier increases. Under the assumed conditions in this scenario, terminal capacity declines and revenue increases for both imports and exports. More in depth analysis, however, is required by terminal operators to estimate the degree of the dependency of CDT on any particular ocean carrier. Terminal operators may use these findings to predict changes in the terminal throughput when ocean carriers change the container volume they handle at that particular terminal.

4.8 Conclusion

In order to expand container terminal capacity, operators have often acquired costly, state of the art technology and container-handling equipment. Simple, inexpensive, yet effective policies, however, may be used to increase terminal throughput capacity. To do so, decision makers must have a better understanding of the factors that determine yard capacity, including CDT. Port operators must be able to delineate between CDT determinants that they can influence and those beyond their control. Understanding these factors assists in estimating CDT. With this information, terminal operators may better manage yard capacity and apply appropriate policies when they are needed. The dissertation developed a generic framework for estimating CDT based on a proposed set of determinants. Three data mining algorithms (Naïve Bayesian, Decision Tree, and an NB-decision tree hybrid) are employed and the results are compared to find the most suitable model for CDT prediction. Using data obtained from a US container terminal, the best performing algorithm-decision tree - was used to measure how changes in the identified CDT determinants can impact the CDT, yard capacity, and terminal revenue. Although no general conclusions can be derived regarding the importance of any factor and it's impact on CDT, this generic approach that can be used in combination with data from any particular terminal to assist in finding potential ways to effectively manage CDT and determine the anticipated impact on terminal capacity and revenue. This research provides members of the port, trade, and transportation community with a useful tool for evaluating appropriate policies to improve the operations of facilities that are an important link in supply chains and a critical connection to the global economy.

Chapter 5 TRUCK GATE VOLUME ESTIMATION BASED ON CONTAINER VOLUME AT APRON USING ANALYTICAL TECHNIQUE

5.1 Introduction

This chapter attempts to correlate and establish a relation between terminals' gate truck traffic and the containers volumes handled at the apron. The findings of the CDT modeling presented in Chapter four are used to investigate how terminal's gate truck traffic are related and affected by the container's features (i.e. CDT determinant factors) and the CDT.

The dissertation delineates potential patterns in the movement of containers between the two external interfaces (i.e. the land side and the seaside). Containers enter or depart from land side by trucks moving through terminal gates; while containers are loaded or unloaded from vessels at the apron in the sea side. In the sea side, containers are processed 24 hours a day, seven days of a week; while the terminal's gates operate on the defined schedule varied among terminals. The dissertation attempts to define the connection and discern the potential patterns between the time and the day (daily and hourly patterns) that the container arrives or departs at the terminal gates and the day that the container is loaded or unloaded from a vessel, i.e. export and import procedure respectively. Figure 5-1 demonstrates the task work flow in relating terminals' gate truck traffic and the containers volumes at the apron. In exploring these patterns, the apron are considered as a starting point (for import and export containers) and the truck's gates are considered as the end point, as defined in the second box of Figure 5-1. The CDT of each container is estimated from the difference between the day and the time of container's arrival in the starting point and the day and the time of container's depart in the end point

using the observed terminal data, as defined in the third box of Figure 5-1. The distribution pattern of the CDT is explored for each day of the apron's operation (box fourth in Figure 5-1). Upon defining this distribution, the day that the container arrives or departs at the terminal gates is estimated and the total number of containers at the gates is calculated on a daily base (box fifth in Figure 5-1). This estimation (truck's volume at the terminal gates) which is derived completely from the CDT distribution of containers at the apron is compared with the observed truck's volumes at the terminal gates to validate the robustness of the selected distribution in estimating daily truck's volume(box sixth in Figure 5-1). In addition, an hourly distribution of truck arrival and departure at gates is explored and defined using the observed data (box seventh in Figure 5-1).

The distribution pattern is also exercised in alternative scenarios, examining the effect of container volume changes at the apron on the truck gates through traffic, and assessing the effect of CDT changes on the truck gates traffic (box eighth in Figure 5-1). The study also estimates the number of truck arrivals and departures at gates on an hourly basis (box ninth in Figure 5-1) for each scenario.



Figure 5-1: Schematic presentation of task 2 procedure

In the following, Section two, the preliminary statistical analysis on the observed data is provided. The outcomes of this analysis will be used in the succeeding sections to identify the CDT pattern and the truck hourly pattern. Section three presents the methodology. Section four applies the developed methodology on the case study, presents the estimation of truck gates volume using the CDT, and derives an hourly truck arrival. Section five develops two practical alternative scenarios following by a summary of findings and concluding remarks.

5.2 Preliminary Statistical Analysis

The observed terminal data used in Task 1 and described in Section 4.3 are utilized in this task to establish the link between two defined areas (sea side and land side). To provide a preliminary investigation on the daily CDT pattern, two main daily groups are created based on the volume of containers serviced at the apron and the gates; weekend, and week day (Mondays through Friday). The reasoning behind that is to examine whether same traffic volumes are expected in weekdays for sea side (Apron) and land side (gates). Same reasoning is considered for weekends. Upon this confirmation, we may generalize that the container volume (at the gates or at the apron) mostly is following the same distribution pattern in each group.

The preliminary statistical analysis, Analysis of Variance (ANOVA) test, is performed on the daily and hourly truck traffic at the gates and a daily number of containers handled at the apron. ANOVA is a statistical test of whether the means of several groups are all equal across one variable (Null Hypothesis). As demonstrated in the following tables (5-1 through 5-8), the ANOVA test estimates the F value, the P value, the sum of squares, and mean squares. The *F* ratio is computed from the ratio of the mean sum of squared deviations of each group's mean from the overall mean. The mean is calculated by dividing the total "Sum of Squares" by the number of degree of freedom. The most important output in the ANOVA test is "*P*" that reports the significance level showing whether there is a difference in means and rejecting the null hypothesis. If the *p*-value is less than the critical value (*a*) set by the experimenter, then the effect is significant. In this study, the "*a*" is set to 0.05; therefore any value less than this will result in significant effects; while any value greater than this value will result in insignificant effects.

The results of the ANOVA test on the inbound truck dataset revealed that no significant changes in truck volumes can be observed between different days of a week (Monday through Friday). The high P-value (p=0.46 > 0.05) in Table 5-1 confirms this hypothesis. Since the truck's gates operate on Saturday and close on Sunday, no grouping weekends (Saturday and Sunday) and ANOVA test have been performed. However, the study of truck's volume for inbound and outbound gates depicts that Saturday's volume is much less than weekdays, as illustrated in Figure 5-2. For the outbound truck traffic, the results demonstrate the same as inbound truck traffic with a better result from Monday through Thursday (p=0.13 > 0.05), as illustrated in Table 5-2.



Figure 5-2: Truck volume percentage on a week

Analysis of Variance on the containers arrived by truck								
Weekday in by truck			Ν		Ν	Iean		
Monday			9		/	2947		
Tuesday				9		3133		
Wednesday		9			302			
Thursda	Thursday		8			-	3124	
Friday			8			2975		
Source	DF	Sum	of Squares	Mean	Square	F Value]	Pr > F
Among	4		248590		62148	0.92		0.46
Within	38		2569492		67618			
	Average scores were used for ties.							

Table 5-1: ANOVA results derived from the number of containers arrived by truck

Table 5-2: ANOVA results derived from the number of containers departed by truck

An	Analysis of Variance on the containers departed by truck							
Weekda	Weekday out by truck			Ν	Mean			
Monday	Monday			9		2980		
Tuesday	7			9	311			
Wednes	day			9		2984		
Thursda	ay			8		3256		
Source	DF	Sum of	Squares	Mean Square	F Value	Pr > F		
Among	3		428462	142821	2.04	0.13		
Within	31		2178178 70264					
	Average scores were used for ties.							

The same analyses are also executed on the number of containers handled at the apron. The results of the ANOVA test reveal that no significant differences can be observed between container volumes shipped or arriving at the terminal on Saturday and Sunday, as demonstrated in Table 5-3(p = 0.75 > 0.05) and Table 5-4 (p = 0.64 > 0.05). Also, weekdays grouping for import and export containers conclude that container volumes do not change significantly on the various days of a week. The results are depicted in Table 5-5 (p=0.73 > 0.05) and Table 5-6 (p=0.47).

Table 5-3: ANOVA results derived from the number of import containers unloaded from

	Analysis of Variance for import containers unloaded from vessel on weekend									
	Weekday in by ship			Ν	Mean					
Sunday			12	12 693						
	Saturday		14 582							
So	ource	DF	Sur	n of Squares Me		an Square	F Value	Pr > F		
A	mong	1		78642		78642	0.11	0.75		
W	ïthin	24		17875203		744800				
Average scores were used for ties.										

vessel on weekend

Table 5-4: ANOVA results derived from the number of export containers unloaded from

vessels on weekend

Analysis	Analysis of Variance on export containers unloaded from vessels on weekend								
Weekday out by ship			NN			Iean			
Sunday			23			573			
Saturday 24					514				
Source	DF	Sum	of Squares	Mean So	quare	F Value	Р	r > F	
Among	1		40735	2	40735	0.23		0.64	
Within	45		8104510	18	30100				
Average scores were used for ties.									

Table 5-5: ANOVA results derived from the number of import containers unloaded from

Analysi	Analysis of Variance on import containers unloaded from vessels on weekdays							
Weekday in by ship			Ν				Mean	
Monday				17			948	
Tuesday				21			891	
Wednesday			25			884		
Thursday			29			594		
Friday						705		
Source	DF	Sum	of Squares	Mean Squ	are	F Value	Pr > 1	
Among	4		2125578	531	394	0.51	0.73	
Within	109		113392845	1040301				
Average scores were used for ties.								

vessels on weekdays

Table 5-6: ANOVA results derived from the number of export containers departed by

	Analysis of Variance on export containers departed by vessels on weekdays								
	Weekday out by ship				Ν]	Mean	
	Monday				25			687	
	Tuesday				26			600	
	Wednesday			25			877		
	Thursday		20				743		
	Friday			24				711	
L.	Source	DF	Sun	n of Squares	Mean S	quare	F Value	P	r > F
ŀ	Among	4		1034153	2	58538	0.89		0.47
١	Within	115		33423998 2		90643			
	Average scores were used for ties.								

vessels on weekdays

The hourly truck traffic examinations revealed that the gates receive an almost the same volume during some time period. The highest P-value depicts that the gates release the same hourly truck volumes at the entrance gates between 10:00 to 16:00 and 7:00 to 15:00 at the departure gates. The outcomes are presented in Table 5-7 (p= 0.65 > 0.05) and Table 5-8 (p= 0.34 > 0.05). The dissertation employs these findings to calibrate the results of an hourly distribution.

Analysis of Variance on Peak hours at entrance gates								
Hour in by	truck			Ν		Μ	ean	
10				50			220	
11				50			205	
12				50			233	
13				50			231	
14				50	223			
15				49			215	
16				43			210	
Source	DF		Sum of Squares	Mea	n Square	F Value		Pr > F
Among	6		31266.35		5211.06	0.6985		0.651
Within	335		2499222.15		7460.36			
Average scores were used for ties.								

Table 5-7: Peak hours at the entrance gates

Table 5-8: Peak hours at the departure gates

Analysis of Variance on Peak hours at departure gates								
Hour out by truck	Ν	Mean						
7	50	198						
8	50	199						
9	50	216						
10	50	202						
11	50	229						
12	50	205						
13	50	222						
14	50	202						
15	50	192						

Source	DF	Sum of Squares	Mean Square	F Value	Pr > F			
Among	8	61340.08	7667.511	1.13	0.3408			
Within	441	2989458.94	6778.818					
Average scores were used for ties.								

The above findings provide adequate evidences to claim that trucks and container's volume at the apron have no significant difference in weekdays and the same assumption can be claimed for weekends as well. An hourly analysis on inbound and outbound truck's volume also revealed that same truck's volume can be expected in some time periods. These outcomes will be utilized in Section 5.4, case study. The following section will discuss thoroughly the procedure of establishing the relationship between container's volume at the apron and truck's gates volume through exploring a pattern on the CDT. This pattern will be used to estimate daily truck volumes at the gates.

5.3 Methodology

In this section, the CDT is used to establish the link between truck gates volume and the container's volume at the apron. The dissertation investigates and defines the existence of a pattern which can be derived from the CDT drawn from the daily apron activities. The derived daily pattern can be used to estimate daily truck volumes at the entrance and exit gates. The terminal data provides an enough knowledge-base to comprehend when containers depart or arrive at the gates on a usual hourly basis. The hourly pattern of truck's arrival and departure is identified at the entrance and exit gates. Finally, the study examines this pattern in the most common and practical scenarios which may occur in a typical container terminal.

5.3.1 Establishment of Link between Gates and Aprons

As stated in Chapter two, trucks arrive at a terminal to pick up their loads (containers), which are unloaded from vessels at the apron earlier, or they arrive to deliver containers, which will be loaded to the vessel later. This procedure is formulated in Equation 5-1. The formula attempts to portray that any departing containers leaving the terminal on trucks on a day "k" (e.g. Feb. 17) and at an hour "h"(e.g. 10:00AM) are unloaded from vessels at the same day or "c" days prior to the day "k". In Chapter four, we limit the "c" duration to ten days (ten classes of CDT) beginning from the same day to 9 days prior to that. Though, the study waives the ten days limitation for the CDT in this task to explore and delineate the pattern comprehensively. By the same token, containers entering through truck gates in a day "k" and hour "h" are loaded onto vessels at the same day or "c" days after day "k".

$$Dt_{Tk} = \sum_{h=1}^{i} Dt_{hk} = \sum_{j=k-c}^{k} \sum_{h=1}^{i} Av_{hjk} \qquad i \ge i' \qquad \text{Equation 5-1}$$

$$At_{Tk} = \sum_{h=1}^{i} At_{hk} = \sum_{j=k}^{k+c} \sum_{h=1}^{i} Dv_{hjk}$$
 $i \le i' \quad c \in P$

Where,

 Dt_{Tk} = Total number of containers that depart on trucks on day k,

 Dt_{hk} = Containers out by truck in an hour *h* on day *k*,

 $Av_{hjk} =$ An import container in by a vessel on a day *j* and hour *h* (*j*≤*k*) and out on a truck on day k.

 At_{Tk} = Total number of containers that enter by trucks on day k,

 At_{hk} =Containers in by truck in an hour h on day k,

 Dv_{hjk} = An export container out by a vessel on a day *j* and hour *h* (*j*≥*k*) and in by a truck on day k,

i= Gate's hour operation,

i' = Apron's hour operation,

k= One working day,

P= Period of available data (two months =60 days for each period of A and B),

c = constant number (0-60 days).

By calculating a number of trucks arrive at the terminal to deliver export containers (At_{Tk}) or pickup import containers (Dt_{Tk}), the truck volume at the entrance and exit gates can be calculated by adding these two values minus a number of trucks performing a dual movement (deliver export and pick up import in the same trip), as shown in Equation 5-2. It is assumed that no truck remains in the terminal after closing the terminal's gates.

$$VG_{in} = VG_{out} = Dt_{Tk} + At_{Tk} - (Dt_{Tk} \cap At_{Tk})$$
 Equation 5-2

Where,

 VG_{in} = Truck volume at the entrance gates,

 VG_{out} = Truck volume at the exit gates, and

 $(Dt_{Tk} \cap At_{Tk}) = A$ number of trucks performing a dual movement.

5.3.2 CDT Calculation

The CDT can be calculated for each container simply by subtracting the container's arrival day (e.g. Av_j) from departure day (e.g. Dt_{ddj}). As mentioned before, the apron is considered as a starting point (day *j* dedicated for inbound and outbound containers at the apron) and the truck's gates are considered as the end point. The CDT is derived from the following equation:

Where,

 CDT_x = The CDT of one export container

 CDT_i = The CDT of one import container

 Dv_j = An export container out by a vessel on a day j ($j \ge d_a$),

 At_{daj} = An export container in by a truck on day d_a and out on a day j by vessel

 $(j \ge d_a),$

 Dt_{ddj} = An import container out by a truck on day d_d and in on a day j by vessel

 $(j \leq d_d),$

 Av_j = An import container in by a vessel on a day j ($j \le d_d$).

j = one working day of apron,

 d_a = Container's arrival date by truck,

 d_d = Container's departure date by truck,

P= Period of available data (two months =60 days for each period of A and B).

Upon calculating the CDT, the CDT analysis will be performed to determine whether any distribution can be fit into the CDT and whether the defined distribution can be utilized to estimated truck volumes at the gates.

5.3.3 CDT Daily pattern recognition

To investigate whether a particular pattern can be derived from the calculated CDT and whether this pattern would be distinctive on different days of the week, all containers arrived or departed at the apron on one day of a week, *w*, throughout the period of study (i.e. two months in period A or period B described in Section 4.3 in the previous chapter)

Equation 5-3

are merged together and make one of seven groups (Sunday through Saturday) of a week. Figure 5-3 demonstrates how these groups are generated for import containers. The same procedure can be drawn for export containers. The procedure starts with sorting the database based on the container's unloading date at the apron. As explained in the Section 4.3, the observed data includes the database of container's arrival and departure for the truck gates and the apron. Some initial settings are established for recording the day of the week, date of containers arrival and the date of truck's departure. In the third box, the first record of database enters into the first group of a week (*w*) from seven groups planned to be established. The CDT is calculated from Equation 5-3. The process, then, follows by reading another record from the vessel database.

After checking that, the record is still in the database and it is not processed, the date of the new record is compared with the existing date of the last record. If the date is same, it means the current record is in the same group of the previous one. Otherwise, it initiates another group and new date is assigned to the reference date of *d*. Finally, If all weekday groups are initiated (seven groups corresponded to seven days of the week), the new week are started from the beginning of the week (w = w + I) and the procedure is reiterated.



Figure 5-3 : Container's grouping based on a day of a week

Upon generating the seven groups of a week, (e.g. Mondays, Tuesdays), different distribution functions, i.e. Beta, Gamma, Normal, Logistic, Exponential, Weibull, Erlang, Lognormal, and Poisson, are fitted on each group.

The results of the above mentioned distribution functions are compared and the Lognormal distribution demonstrates the best fit. Nevertheless, all distributions have shown their shortcoming in modeling Saturday and Sunday behaviors, since those days are presented different behavior compared with other days on the weekday as shown in Section 5.2.

Lognormal distribution is a single-tailed probability distribution of any random variable (x = CDT) whose logarithm is normally distributed (y = ln (x = CDT)).

The probability density function of the Lognormal (μ, σ) is

$$f(x) = \frac{1}{x\sigma\sqrt{2\pi}} e^{\frac{(\ln(x) - \mu)^2}{2\sigma^2}} \quad \text{With } x, \sigma > 0 \quad \text{Equation 5-4}$$

Where,

$$x = CDT$$
,

 σ = Shape parameter or standard deviation of the CDT's natural logarithm, or standard deviation = $((Exp(\sigma^2) - 1)Exp(2\mu + \sigma^2))^{1/2}$, and

 μ = Mean of the CDT's natural logarithm or Mean = Exp ($\mu + \sigma^2/2$).

This distribution assists in developing alternative scenarios estimating the change in the number of trucks at the gates when the number of containers handled at the apron increases (Scenario 1 presented in Section 5.4.1) and when the CDT decreases (Scenario 2 presented in Section 5.4.2).

Lognormal distribution fitting theorem

Lognormal distribution, which is used extensively in reliability applications to model failure times, presents the superior fitted distribution compared to other distributions. The reasoning behind this functioning can be interpreted to the shape of this distribution. The Lognormal distribution has an appealing form with a modal response strictly above zero, asymmetric shape, and a long tail captures infrequent cases when containers remain in the yard for a long period of time. The lognormal distribution shape also spreads out, as the standard deviation (σ) increases and narrow down when the standard deviation decreases, as demonstrated in

Figure 5-4.



Figure 5-4: Lognormal distribution function shape - Extracted from "StatSoft- Electronic Statistics Textbook"¹⁰

This functionality can explain the CDT behavior when the CDT has more variance around mean and when the CDT has less variance and close to the mean. This characteristic is particularly used in the second scenario discussed in Section 5.5.2.

¹⁰ StatSoft- Electronic Statistics textbook , <u>http://www.statsoft.com/textbook/distribution-fitting/#log-normal</u>, Accessed March 2010.

5.3.4 Truck Volume Estimation Using CDT

Truck volumes at gates can be calculated using the CDT estimated from the outcomes of the fitted distribution. The following equation can be used to derive truck volumes at the inbound and outbound gates using the CDT.

$$AT_k = \sum_{i=k}^{k+j} XCDT_{(i-k)k}$$
 Equation 5-5

$$DT_k = \sum_{i=k-j}^k ICDT_{(k-i)k} \quad \forall k, j \in P$$

Where,

 AT_k = Total number of containers arrive in a day k at the inbound gates,

 $XCDT_{ik}$ = Number of export containers with the CDTs of "*i-k*" departed by vessel in days between *k* and *k+j* and arrive in day *k* by truck, ($j \ge k$)

 DT_k = Total number of containers depart in a day *k* at the outbound gates,

 $ICDT_{ik}$ = Number of import containers with the CDT of "*k*-*i*" arrived by vessel in

days between *k*-*j* and *k* and depart in day *k* by truck, $(j \le k)$

j=A day that container left/arrive the terminal by vessel,

k = one working day at the gates, and

P = Period of available data (two months =60 days for each period of A and B)

5.3.5 Hourly pattern recognition

The CDT daily pattern can be used to estimate the daily truck volumes at the entrance and exit gates as a function of the number of containers processed at the apron. Nevertheless, it does not provide enough of a knowledge-base to comprehend how containers depart or arrive at the gates on an hourly basis. To examine this aspect, once again, the data for each day of a week is grouped together (e.g. Mondays, Tuesdays, and etc) and hourly truck gate activities are drawn for each group using the terminal data. As stated in Section 4.3, the exact arrival and departure time of containers at the truck gates was available through the actual. The grouping was performed to explore whether a distinctive hourly pattern can be derived for each day of a week. Figure 5-5 demonstrates how these groups are generated for containers arrived at the entrance gates. Same procedure can also be deployed for the outbound gates (import containers). Based on this procedure, the truck's arrival database is sorted based on the date, hour, and minute of arrival. Some initial settings will be established for recording the day of the week, date, and the hour of containers arrival (6:00AM gates open). An hourly number of trucks are derived by adding all containers arrived in a 60 minutes and put it in the first group of a week. After processing one hour, a next hour will be processed till one day of a work is finished (h = 22; gates close). Then, the day counter (d) will change to the next sevenday (d=d+7) to compile all records in the one group of a week (e.g. all records of Mondays). When all records of one group is read and processed, another group will be initiated (w = w + I) and processed from the beginning. Upon generating the seven groups of a week, (e.g. Mondays, Tuesdays), different distribution functions, i.e. Beta, Gamma, Normal, Logistic, Exponential, Weibull, Erlang, Lognormal, and Poisson, are fitted on those groups. The Poisson distribution yields the best fit to model hourly truck gate activities particularly for a specific time period (defined in the following section).



Figure 5-5: Container's grouping in hourly bases

The Poisson distribution is a discrete probability distribution that expresses the probability of a number of events occurring in a fixed period of time. These events,

which occur in a fixed period of time, are independent of the time of the last occurrence. If the expected number of occurrences in this period is λ , then the probability of having x occurrences is

$$p(x) = \frac{\exp[(-\lambda)\lambda^x]}{x!}$$
, with $x \in \mathbb{N}$ and $\lambda > 0$ Equation 5-6

Alternative scenarios retain this distribution for estimating hourly truck volumes when the number of containers processed at the apron escalates or the CDT changes. This distribution is also employed in the modeling of the entrance gates in the ARENA simulation environment.

Poisson distribution fitting theorem

The Poisson distribution which is sometimes referred to the distribution of rare events is mostly used in queuing systems' characteristics such as arrival and departure processes. This distribution can capture hourly truck arrivals, because of the following associated characteristics between hourly truck arrival and Poisson features;

- The event in Poisson is discrete and can be counted in whole numbers, as it is in truck arrival.
- The occurrence of events is independent; therefore, one occurrence neither diminishes nor increases the chance of another, as it is in truck arrival at the terminal gates.
- The average frequency of occurrence for the time period in question is known. Though, truck arrival has completely random nature, the average frequency can be estimated from the historical data.

5.3.6 Alternative Scenario Establishment

The patterns discovered in daily and hourly truck arrivals and departures assist the author to develop two alternative scenarios exploring the applicability of the proposed model in the common and practical scenarios, which may occur in a typical container terminal: increases in container volume at the apron and changes in the CDT.

The first scenario assumes that the CDT pattern (Lognormal distribution) has not been changed as the number of containers is increased by 50% at the apron. The second scenario probes changes in truck gate volumes when container volumes at the apron remain the same but the mean CDT and its standard deviation change (the parameters of Lognormal distribution).

The following steps are taken into the consideration to develop and execute the first scenario:

- 1. Find the current number of containers at the apron and increase them by 50%.
- 2. Apply the current mean and standard deviation of Lognormal distribution for each weekday group.
- 3. Generate Lognormal distribution with the parameters defined in Step 2 and container volume defined in Step 1 to create a random number of containers in each CDT class per container group.
- 4. Derive the number of trucks at gates using the procedure described in Figure 5-3 for grouping and Equation 5-5 for the truck volume estimation.
- 5. Find the current parameters of Poisson distribution for each weekday group. Derived from the actual data, the average mean of this distribution " λ " is 12

trucks/h (i.e. $11 < \lambda < 13$) for import containers and 11.5 trucks/h ($10 < \lambda < 12$) for export containers for all weekday group.

- 6. Perform pattern justification for hourly truck arrival by observing the real data behavior. Deriving from the actual data, the arrival and departure of trucks in some periods can be assumed to follow the uniform distribution, since a number of trucks don't change significantly in these periods (proven by the ANOVA test discussed in Section 5.2).
- Compute an hourly number of trucks based on the outcomes of the pattern justification performed in step 6.
- 8. Conclude how the increase of the container volume at the apron affects the through traffic at the gates.

The following steps are performed for the second scenario.

- 1. Find the current number of containers at the apron.
- 2. Halve the mean CDT and the standard deviation derived from the application of Lognormal distribution on each daily group.
- 3. Generate Lognormal distribution with the new parameters defined in Step 2 to create the number of containers in each CDT class. The container volume of the base case scenario is considered in this scenario.

Go to Step 4 of the previous scenario.

In the following section, the technique developed in this section will be applied on the observed data examining and confirming the patterns identified for the CDT and trucks hourly rates.

5.4 Case study

The observed data defined and described in Section 4.3 is used to examine the robustness of the technique developed in the previous section. Different distribution functions are fitted on the dwell time of containers processed at the apron (inbound and outbound containers) and the result of the selected distribution function (Lognormal distribution) presents its fitness in capturing the CDT pattern compared with the other distributions. The outcome of this distribution function, then, is utilized to estimate truck volumes at the terminal gates. In addition, an hourly truck pattern will be drawn to examine how the estimated truck volume is arrived or departed in an hourly base.

In this case study, the following data fields are used among the existed data fields described in the Section 4.3:

- Exact date and time of arrival and departure at the apron, and
- Exact date and time of arrival and departure at the truck gates.

5.4.1 CDT Daily Pattern Investigation

As mentioned in the preceding section, the apron's operational days are grouped for each day of a week (Mondays, Tuesdays, ..., Sundays) using Figure 5-3. Table 5-9 shows one sample group for Friday export containers. The first column (Date out by vessel) of Table 5-9 shows the dates that containers are loaded on to vessels. As one can observe, all dates are referred to the Fridays of the period of the study (Period B = Jan. 2007 to Feb. 2007). The second column (Date in by truck) shows the date that containers were delivered at the terminal by trucks. Finally, the third column presents the CDT (*CDT_x*) estimated from Equation 5-3.

Date out by vessel	Date in by truck	Dwell time
2/9/2007	2/2/2007	7
2/2/2007	1/23/2007	10
1/5/2007	1/5/2007	0
1/5/2007	1/4/2007	1
1/26/2007	1/24/2007	2
2/9/2007	2/5/2007	4
2/2/2007	1/26/2007	7
2/16/2007	2/8/2007	8

Table 5-9: Friday group for export containers

For each weekday group, all distributions (Beta, Gamma, Normal, Logistic, Exponential, Weibull, Erlang, Lognormal, and Poisson) are tested against the CDT. Although none of them passed the chi square goodness of fit, as illustrated in Table 5-10, Lognormal distribution delineates better results than the other distributions.

	Chi-square (Observed value)	Chi-square (Critical value)
Weibull	9570.74	37.65
Beta	12893681.24	37.65
Poisson	102707592.64	28.87
Exponential	16284.25	41.34
Negative Binomial	8005.12	40.11
Erlang	96716.07	40.11
Normal	278182930372638.00	16.92
Gamma 1	1071779.27	41.34
Logistic	16571.17	40.11
Lognormal	6772.15	40.11

Table 5-10: Distribution results extracted from one set of data

The reasoning is the atypical characteristic of Saturday and Sunday activities in the terminal. As shown in Figure 5-2, truck gates have insignificant activities on Saturday and the terminal's gates are closed on Sunday. Simultaneously, a smaller number of vessels are berthing on the weekends as compared with the weekdays as shown in Table 5-3 and Table 5-4. Consequently, no distribution functions can capture this irregular
behavior. To validate this reasoning, different CDT intervals (i.e. one class, two in one class, and three in one class) are examined against the observed data. The creation of intervals is performed to eliminate or diminish the irregular behavior of the gates and the apron on the weekends. Integrating two or three CDT classes in one interval improved the chi-square results as illustrated in Figure 5-6; a) one CDT per interval, b) two CDT per interval, c) three CDT per interval, and d) Chi square results for all intervals. More investigations and illustrations on import and export containers for each daily group are presented in Appendix 3. In these illustrations, the x –axis presents different classes of CDT (one day for each bar (a), two days on each bar (b), or three days on each bar (c)) and y-axis presents the density which is the number of the actual data in each CDT class to the total number of containers in each weekday group.



Interval a	Chi-square (Observed value)	6364.94				
Interval a	Chi-square (Critical value)	40.11				
Interval b	Chi-square (Observed value)	2614.42				
Interval b	Chi-square (Critical value)	21.03				
Interval c	Chi-square (Observed value)	1179.28				
Interval c	Chi-square (Critical value)	14.07				
(d)						

Figure 5-6: The fitted Lognormal distribution for a) one CDT per interval, b) two CDTs per interval, c) three CDTs per interval, d)Chi square results

These findings are used in the alternative scenarios to estimate the daily number of containers at gates.

5.4.2 Truck Volume Calculation

The findings of the fitted distribution provide the number of estimated containers in each class of CDT (starting at the apron and ending at the gates), which leads us to the number of containers leaving or entering the terminal at gates using Equation 5-5. Table 5-11 depicts the actual and estimated frequencies derived from the Lognormal distribution applied on the CDT of the Monday group. The first column of the table shows the CDT classes; the second and the third columns show the least and the highest value of the CDT classes respectively. The fourth and fifth columns show the actual and estimated number of records respectively in each class of CDT in the Monday-group database. Chi-square value showing the goodness of fit of an observed value to a theoretical one depicts in the column sixth. As shown in Table 5-11, the estimated frequency derived from the distribution is comparable to the actual data, excluding Saturday and Sunday (shown in class two, three, nine, and ten), which contributed to the high chi-square values. These findings also provide an evidence for the utilization of this distribution in capturing the CDT parameter assigned to each entity in the simulation approach. In this example, trucks are delivering export containers for vessels.

					Chi-
Class	Lower bound	Upper bound	Frequency (Data)	Frequency (Distribution)	square
1	0.000	1.000	76	51	12.408
2	1.000	2.000	0	370	370.211
3	2.000	3.000	39	871	794.906
4	3.000	4.000	1588	1229	105.040
5	4.000	5.000	1750	1335	129.353
6	5.000	6.000	1602	1252	97.642
7	6.000	7.000	1583	1077	237.460
8	7.000	8.000	995	878	15.607
9	8.000	9.000	0	691	691.417
10	9.000	10.000	26	533	481.968
11	10.000	11.000	406	405	0.004

Table 5-11: Monday- group– Export procedure (Period B)

These trials define the parameters of Lognormal distribution for each group, Mean and Standard deviation, which will be utilized in the next section to develop the alternative scenarios.

One day from each weekday group is selected randomly in period A or B to evaluate the validation of the distribution's outcomes comparing with the observed gates data. This procedure is performed for both import and export procedures and the findings are illustrated in Table 5-12. The calculation of gate volumes utilizing Equation 5-5 requires extracting data from at least 70 different days (at least 10 days prior to vessel arrival and seven weekday-groups). Table 5-12 compares the estimated (column two) and the actual (column three) number of containers in each group of weekday (column one). The broader extent of this scenario is investigated and discussed in the next task presented in the next chapter.

Weekday	Estimated	Actual
Monday	1142	1357
Tuesday	1696	2284
Wednesday	1729	1944
Thursday	1772	2089
Friday	1430	2083
Saturday	1207	80

(a) Export Procedure

	Table 5-12 Con	nparing the	estimated g	gates truck	volume	with the	observed	data
--	----------------	-------------	-------------	-------------	--------	----------	----------	------

Weekday	Estimate	Actual
Monday	1337	2144
Tuesday	1096	1865
Wednesday	1762	2505
Thursday	3504	4217
Friday	2713	2980
Saturday	1001	131

(b) Import Procedure

It appears that the Saturday estimation is completely unrealistic, though the rest of estimations present the better result. This is more evident on the export procedure. The percentage of errors comparing with the actual data fluctuated from 8% to 40% for import containers and from 11% to 30% for export containers. The result of this study

can facilitate the estimation of gate volume using the apron volume, which has more defined schedule. In addition, this distribution can also provide a better view of yard capacities based on the pattern discovered from the CDT distribution.

5.4.3 Hourly Pattern Investigation

As demonstrated in Figure 5-5, the process of weekday grouping is deployed to produce hourly patterns of truck traffic at the gates for each working day. Upon examining all distributions defined in the Section 5.3 on the observed data, the Poisson distribution exhibits the better results; nevertheless, this distribution shows its shortcoming in modeling the first hours of gate opening. An assessment of the results of Table 5-7, Table 5-8, and Figure 5-7 reveals that the arrival and departure gates follow the uniform distribution in some period between 7 to 16 (10:00-16:00 in entrance gates and 7:00-15:00 in departure gates), since the container volumes do not change significantly (proven by ANOVA test).

Uniform distribution which can be classified to two categories; discrete, and continuous refers to the finite set of possible values in the specific time interval (a, b) that all values are equally probable. As proven by the ANOVA test, the assumption can be made that all probable values are same in the specific time interval. In this study, the interval is defined in the period of 10:00-16:00 (a, b) for entrance gates and 7:00-15:00 (a, b) for departure gates.

On the other hand, the Poisson distribution represents well the gates' behavior on the afternoon and evening hours (~16 to 22). Appendix 4 exhibits the findings of Poisson fitting on all weekday groups.

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Figure 5-7: Hourly distribution of containers at gates for Tuesdays group

The Uniform and Poisson distribution are utilized in the alternative scenarios to disseminate the daily estimated trucks in an hourly base. These tactics (uniform in the peak period and the Poisson in afternoon and evening) are also chosen to represent truck arrivals at the gates in the ARENA, simulation tool.

The results of Poisson distribution representing the departure and arrival of trucks in an hourly basis delineates the mean of this distribution " λ " (i.e. $11 < \lambda < 13$ with the average of 12 for import; $10 < \lambda < 12$ for export with the average of 11.5) for each weekday group. These means will be utilized in the alternative scenarios.

5.5 Development of Alternative Scenarios

As noted above, the alternative scenarios are designed to examine how CDT analyses and the established link between the apron and gates can mimic the real conditions and examine the robustness of the developed model through the application of this model in practical scenarios. The first scenario assumes that the CDT pattern (Lognormal distribution) has not been changed as the number of containers is increased by 50% at the apron. This assumption can be made based on the reasoning presented in the Section 5.3 (Lognormal distribution fitting theorem). It is also important to note that, this is not the only study investigating the CDT pattern. Bakshi et al. (2009) studied the CDT pattern to estimate the operational impact of container inspections at the international ports. He found out that the CDT of two terminals under study follows the Lognormal distribution with different parameters. He derived this pattern on the CDT of containers departing terminals on a one month period. The discussion can be made that the CDT pattern may follow the Lognormal distribution; though, the parameters (CDT mean and variance) may change due to the expectation of more truck picking up or delivering containers. This is actually what it will be addressed through this scenario. The scenario attempts to demonstrate if this parameter doesn't change and more trucks are expected to pick up their loads (as they do) what will be the consequence of this action and what will be the number of containers at truck gates on a daily basis.

The second scenario probes changes in truck gate volumes when container volumes at the apron remain the same but the mean CDT and its standard deviation change (the parameters of Lognormal distribution). As discussed in the first task, changes in the container status or ocean carrier (CDT determinant factors) alter the CDT. This scenario investigates whether the change in the CDT will impact truck gate activities. To change the CDT in the distribution model, the mean CDT and standard deviation of Lognormal distribution is halved without any changes in the apron's container volume. The parameters' justification is performed to reflect that more containers arrive or depart during the first days (i.e. CDT class of two days or less) with less variance. This

examination, once more, will be considered in the next chapter to validate and compare the results of the fitting distribution model in the simulation approach.

5.5.1 Scenario 1: Increase the apron's volume

In this scenario, the number of containers loaded and unloaded at the apron is increased by 50%. For each defined day, the mean and standard deviation of Lognormal distribution of that day, along with the new container's number at the apron, feed into the Lognormal distribution, generating the new set of CDT data to derive the number of containers at the gates and examine the impacts of the apron's volume increases on the truck gates volume.

Table 5-13: Comparison of truck volume in different scenarios at the entrance gates

Weekday	Scenario1-Increase volume by 50%	Estimated- Base case	Actual
Monday- day x	1767	1142	1357
Tuesday- day x ₁	2593	1696	2284
Wednesday- day x ₂	2960	1729	1944
Thursday - day x ₃	2478	1772	2089
Friday - day x ₄	1682	1430	2083
Saturday - day x ₅	2063	1207	80

Table 5-14: Comparison of truck volume in different scenarios at the departure gates

Weekday	Scenario1-Increase volume by 50%	Estimated- Base case	Actual
Monday- day x	2059	1337	2144
Tuesday- day x ₁	1718	1096	1865
Wednesday - day x ₂	2500	1762	2505
Thursday - day x ₃	4832	3504	4217
Friday - day x ₄	4354	2713	2980
Saturday	1641	1001	131

The findings demonstrate that a 50% increase in the apron's volume will result in almost

50% increase in the gate activities, as we expected (comparing column two and three in

Table 5-13 and Table 5-14). Clearly Saturday results demonstrated an unfitness of the model, as shown in the base case estimation (defined in red in Table 5-13 and Table 5-14).

To derive an hourly distribution of containers at the entrance gates, the dissertation utilizes the outcomes of ANOVA test presented in the Section 5.2 and the outcomes of Poisson distribution presented in the Section 5.4.3.

As ANOVA test results demonstrated (presented in Section 5.2), the average number of containers at gates has no significant difference for different days of the week (Monday through Friday). Therefore, the number of containers for one day in weekdays is estimated from averaging day x to day x_4 . An hourly distribution of containers at the gates (entrance and departure) is derived for this average. The Poisson distribution is generated for the average daily number of containers based on the mean (λ =11.5 for export and $\lambda = 12$ for import) calculated in the Section 5.4.3. The fitted data related to this distribution is employed on an hourly arrival of containers at the gates in the early hours of the gates operation (6:00-9:00) and the late hours (17:00 - 22:00). This distribution is also applied on an hourly departure of containers at the gates in the early hour of the gates operation (6:00 - 7:00) and the late hours (16:00 - 22:00). The uniform distribution is assumed for the time period of 10:00 to 16:00 for the entrance gates and 7:00 to 15:00 for the departure gates based on the ANOVA test results. The number of containers for this period is estimated by dividing the total number of containers arriving by truck in these time periods by the number of hours (i.e. number of hours between 10 and 16 for arrival and between 7 and 15 for departure).

The comparison between the total number of containers obtained from the Poisson distribution and the number of containers obtained from the above assumption depicts minor differences (~40-90 containers in about 2000 containers).



Figure 5-8: The hourly distribution of truck arrival at the gates



Figure 5-9: The hourly distribution of truck departure at the gates

5.5.2 Halve the CDT and its standard deviation

In this scenario, the mean number of CDT and the standard deviation defined in the Lognormal distribution for each day are halved. The standard deviation is halved in order to examine what will occur if more containers arrive or depart in a very limited time period and how the gates (entrance and exit) will respond to this change. The number of trucks at the gates is derived using the new CDT pattern (Log normal distribution with the new parameters). Table 5-15 and Table 5-16 depict these outcomes.

	Scenario2-		
	Decrease CDT by	Estimated-	
Weekday	half	Base case	Actual
Monday	1364	1142	1357
Tuesday	1698	1696	2284
Wednesday	1778	1729	1944
Thursday	1621	1772	2089
Friday	1591	1430	2083
Saturday	1513	1207	80

Table 5-15: Comparison of truck volume in different scenarios at the entrance gates

Table 5-16: Comparison of truck volume in different scenarios at the departure gates

	Scenario2-		
	Decrease CDT by	Estimated-	
Weekday	half	Base case	Actual
Monday	2019	1337	2144
Tuesday	1720	1096	1865
Wednesday	2443	1762	2505
Thursday	4065	3504	4217
Friday	2414	2713	2980
Saturday	904	1001	131

The comparison revealed that more containers have to be handled at the gates even when the number of containers has not been changed at the apron. In this scenario, the increase of activity at the departure gates is more extreme than the entrance gates, since the average CDT for import containers is less than export containers. Therefore, the CDT reduction provides more containers in a slim period of time at the gates. This scenario is also examined in the simulation approach, demonstrating rather longer truck turn times due to the gates overcrowding. A more elaborate discussion will be offered in the following chapter.

The procedure performed in scenario one is also executed in this scenario to extract an hourly container distribution at the gates, as illustrated in Figure 5-10 and Figure 5-11.



Figure 5-10: Hourly distribution of truck arrivals at the gates



Figure 5-11: Hourly distribution of truck departures at the gates

The hourly comparison between this scenario and the estimated base case revealed that, as we expected, more containers have to be processed at the gates in each time period. Again, this behavior is more obvious for import containers. Figure 5-12 and Figure 5-13 present the hourly comparison of truck arrivals and departures at the gates for actual, the estimation of actual, scenario one, and scenario two.



Figure 5-12: Hourly comparison of truck distributions at the entrance gates in different

scenarios



Figure 5-13: Hourly comparison of truck distributions at the departure gates in different

scenarios

5.6 Conclusion

It is an evident that there is a relation between the apron's container volume and truck gates traffic. Trucks arrive at the terminal to pick up or drop off its load delivered or carried away by a vessel in a particular time frame. Nevertheless, this relation is indirect; the study attempts to derive the relation between the time that containers are debarked or embarked from vessels and the moment that containers depart or arrive at gates. The CDT is utilized to estimate trucks volume at the gates based on the apron's volume. Though, the study discovered that no robust and statistically proven fitted distribution (daily and hourly) can be found because of atypical behavior of containers in weekends and at the peak hours, the suitable distributions found that can estimate trucks volume at the gates reasonably well in the daily and hourly base comparing with the terminal data.

Using the determined distributions, the truck volumes at the gates are estimated and the results are comparable with the terminal data. Different scenarios are also developed to examine how the increase of a number of containers at the apron and the CDT changes can affect truck traffic volume at the gates.

Chapter 6 TRUCK GATE VOLUME ESTIMATION BASED ON CONTAINER VOLUME AT APRON USING SIMULATION

6.1 Introduction

The dissertation employs a simulation technique to model the gates, truck interchange area, yard, and apron operations at a macro level. This macro simulation phase attempts to 1) examine and validate the analytical findings derived in the previous tasks (e.g. the effect of CDT on truck traffic at gates, CDT pattern), and 2) investigate the aptness of an appointment system to ease the congestion at truck gates. The base scenario is developed using typical movements of containers in marine container terminals and calibrated utilizing the actual data. Different scenarios are proposed and developed for the existing condition (based case). Then, the study focuses on initiating the appointment system at the terminal gates and the truck interchange area. The expansion of the appointment system beyond truck gates is expected to not only ease the congestion at the terminal gates particularly in peak periods but also reduce truck handling at the interchange area. Different appointment system scenarios are also examined based on different operation strategies, demand level and supply size. Five major factors are considered to measure terminal performances in all scenarios including the base case and a proposed one; delay at the gates, delay at the truck interchange area, queue length at the gates, transfer equipment utilization factor, and truck turn time.

The dissertation utilizes the ARENA simulation application to create the simulation model. Arena is a simulation software package with the capability of modeling procedures, analyzing future performances, and visualizing operations.

The chapter is organized as follows; the design and implementation of the simulation model is discussed in the following section including the initiation of different modules, terminal performance factors, and the calibration procedure. After that, the base model and the appointment system is designed and deployed along initiating and developing different scenarios.

6.2 Design Procedure

Though, the simulation model is designed based on the typical operation of container processes in the entrance, yard, truck interchange area, exit gates, and the apron, the dissertation focuses on developing various scenarios at the terminal gates and truck interchange area in a macro level. Six major modules are initiated to build the base model in ARENA: trucks arrival, entrance gate (pre-gates and main gates), interchange area, yard, apron, and departure gates. In designing the simulation model, trucks are loaded or unloaded at the interchange area (not at the yard).

ARENA is a set of modules and blocks (e.g. entities, attributes, variables and resources) each being hard-coded in SIMAN (Soft ware language). These modules/blocks are combined and connected to each other to build a simulation model of a physical system. The software analyzes a wide range of factors to demonstrate, predict and measure system performance (Bapat et al., 2001). ARENA is also capable of doing dynamic analysis that captures the effect of variability through different time periods (e.g. by assigning different scheduling to each entity in every second). Dynamic analysis can predict the effects of random downtimes, as well as demand, and loss on the system advantage over static modeling tools which typically use averages or deterministic values in their mathematics, causing the solutions to be optimistic performance assessments.

Two phases are established in a designing stage; a calibration, and an application. In the first phase, the observed data is used to create and send entities (truck and vessel) into the base model. In this phase, the service rates in each service area (e.g. gates, truck interchange area) in the terminal are adjusted considering Truck Turn Time (3T) which is available from the observed data. Upon the calibration of service rates, the second phase is deployed the distribution functions to create trucks and vessels, and estimate the CDT. This is a based model, which will be utilized in different scenarios including an appointment system. Figure 6-1 depicts the process of truck services from the arrival time till departure at gates. As illustrated, the cylinder shapes define the variables and required data that some of them are estimated from the actual data (e.g. status of container, dwell time). The assumptions have been made for the rest of the variables (e.g. transfer equipment) based on the previous research or common current practices. In the following section, each module will be covered separately and discussed thoroughly.





Figure 6-1: The procedure of truck services at the terminal

6.2.1 Trucks Arrival Module

Typically, trucks arrive at the gates with three possibilities: 1) to drop off the export containers and leave the port; 2) to drop off export containers (full or empty) and pick up import containers; 3) to enter with their chassis and pick up imports or empty containers. To generate trucks and enter them into the base model, the investigation on the most robust distribution function is performed. The preliminary analysis on the observed data is revealed that the Beta distribution is the best fitted distribution comparing with other examined distribution functions, i.e. Beta, Gamma, Normal, Logistic, Exponential, Weibull, Erlang, Lognormal, and Poisson. As defined before, Lognormal distribution would be a suitable probability distribution for the CDT of export containers expected daily at the gates. It is worth to mention that, the CDT attribute is checked for each entity before transferring from yard to the truck interchange area or the apron to load onto a truck or a vessel. Since the terminal under study opens weekdays for 16 hours (6:00 AM - 10:00 PM) and Saturday for 8 hours (8:00 AM- 16:00 PM), this schedule is also reflected in the truck scheduling. Besides trucks carrying empty or full containers, the simulation model also considers the arrival of trucks with chassis. Since data is not available for these trucks, the Poisson distribution is assumed as their arrival rate. The characteristic of this distribution makes this distribution to be a good fit, as described in Section 5.3.

6.2.2 Entrance Module

Figure 6-2 depicts the procedure of container's services at the entrance gates. Two entrance gates are designed to process arriving trucks: pre-gates with five booths and main gates with ten booths. In the beginning, trucks arriving from the arrival module are assigned to each pre-gate booth based on the minimum number of existing trucks per queue per booth and the idleness of the booth. Pre-gates are assumed to check the truck's paper work and gates are assumed to inspect trucks and their containers thoroughly and assign the interchange areas to trucks for loading or unloading their containers. If there is a problem with a truck's paper work or its container, as shown in the second box of Figure 6-2, the truck is referred to the customer service to solve the problem. Trucks are randomly selected and sent to the customer service based on the probability rate (*x*). The travel time between the pre-gates and the customer service, and the service rate in the customer services also have to be determined for the model (the first and the second box after the "Yes" condition outlet in Figure 6-2). Trucks with no problems are directed to the entrance gates where the interchange areas are assigned (the first box after the "No" condition outlet).

The service rate at pre-gates and gates are assumed to follow the Exponential and Poisson distribution¹¹. To find the most appropriate service rate at the entrance module (gates and pre-gates), the average of Truck Turn Time (3T) obtained from the actual data is utilized to train the model.

Considering the level of workloads at pre-gates, gates, and the average of 3T, the mean of the Exponential and Poisson distributions are estimated for pre-gates and gates services. The simulation model also assigns each entity to each entrance booth based on the minimum number of existing number of entity per queue per booth and the idleness of the booth. Figure 6-2 illustrates the entrance module created in ARENA.

¹¹ The same assumption was made by Liu et al 2002, Rizzoli et al 2002, Maksimavicius 2004, and Meyer 2004.



Figure 6-2: Entrance module designed in ARENA

6.2.3 Truck Interchange Module

After assigning interchange areas to trucks, trucks are directed to the interchange area (the first box in Figure 6-3). Trucks are assigned to twenty interchange locations based on their availability (the second box in the figure). If a truck is dropping off an empty or full container, a request for a Transfer Equipment (TE) is sent to unload or strip the truck from its container. In case that a truck with chassis requests a service, only the loading service is processed. In case that a TE is not available (the first condition box), the truck remains in the interchange area till the TE gets free and ready to serve the truck. On the

other hand, if there is an idle TE to serve the truck (Signal = 1, the first box of "Yes" condition outlet), the truck's status is checked for an unloading process. If the truck contains a container to be unloaded, the TE performs the truck unloading procedure and the TE drops off the container at the yard. If the double-movement (unloading and loading) for that truck is requested, the truck loading procedure is also performed. After completion of serving the truck, the TE sends the ready signal to announce its idleness. It is important to note that, containers are being released by their dwell times. The TE picks up a container that its dwell time is equal or bigger than the simulation running time. After that, the TE loads the container onto the truck in the interchange area and sends the free signal indicating its ability to serve. Once the loading/unloading of trucks is completed at the interchange area, the trucks proceed to the exit gates.

The TE service rate is assumed to follow the Exponential distribution for picking up or dropping off a container¹². As explained before, the mean of exponential distribution is calculated through training the model in the calibration phase considering the average of 3T. Figure 6-3 illustrates the truck interchange module created in ARENA.

¹² The same assumption was made by Meyer 2004 and Hartman 2004.



Figure 6-3: Truck interchange module in ARENA

6.2.4 Yard Module

The yard module where the import and export containers are temporary stored is a buffer link between the apron module and the interchange area module. Both, the apron and the interchange area, modules drop off containers at the "Hold" element (i.e. yard) and TE searches this unit to find containers, which their dwell times are equal or bigger than the simulation time. The service rate for a yard crane is also assumed to follow the Exponential distribution, since the location of a container at the yard block imposes the yard crane to do some unproductive movements (reshuffling) to obtain the container in the particular block. Figure 6-4 demonstrates the pseudo algorithm of the yard module applied in the simulation model.

/* Yard Module Procedure*/

Yard receives container
Hold the Container
Record container aweil time (CDI)
<i>IE receives a request for a container</i>
Signal =1
Loop /* Search all containers in yard
<i>If "CDT > simulation run time" & "Interchange area TE request a container"</i>
then
TE load the container
Transfer to the interchange module
Signal =0
Else if " $CDT > simulation run time" & "Apron TE request a container" then$
TE load the container
Transfer to the Apron module
Signal =0
Else /* CDT < simulation time
The container is being hold in yard
EndIf
If $signal = 0$ then
Exit loop
Else
record = record+1 /* Search for another container
endif
Endloop

Figure 6-4: Pseudo algorithm applied in the yard module

6.2.5 Apron Module

Vessels arrive at the terminal with import loads 24 hours a day, 7 days a week. In this study, the exact time and the vessel's inter-arrival time are not under consideration. The simulation time for import containers starts ticking when the containers are at the apron. Since the vessels unloading data was available from the terminal being studied, the actual data is utilized to send vessels into the simulation model in the calibration phase (first box in Figure 6-5). Though, the service rate at the apron is not available for the calibration of this module in the simulation model, the 3T data which is available from the observed data is utilized to do the adjustment on the apron's service rate. The logic behind this utilization is the availability of TEs. The intensive workloads at the apron could delay the services at the yard and the interchange due to the unavailability of transfer equipment; consequently, it influences the 3T. This connection is utilized to adjust the service rate at the apron in some extent. The outcomes extracted from the actual data demonstrate that the container's dropping off process follows the Beta distribution and the CDT of import containers follows the Lognormal distribution. The procedure of container handling at the apron is similar to the interchange area processes. A container sends a request signal to be serviced by a TE at the apron (first conditional box in Figure 6-5); an idle TE replies to the service request by picking up the container at the apron (the first process box after the "Yes" condition outlet) and transferring it to the yard. If the CDT is equal or bigger than the simulation time, the container is transferred from yard to the apron by the TE. After releasing the container at the apron, the TE sends the idle signal showing its availability to serve (the last signal in Figure 6-5). Figure 6-5 illustrates the procedure of vessel's arrival at the apron module created in ARENA.



Figure 6-5 : Vessel's arrival module created in ARENA

The procedure of loading containers onto the vessel is similar to the unloading procedure with the difference in the direction processes (from the yard to the apron).

6.2.6 Departure Module

After trucks have been serviced at the interchange area, trucks are driven to the exit gates (the first box in Figure 6-6). At the exit gates, containers and trucks are monitored for any mishandling, including paper work and the physical condition of containers, before leaving the terminal (the second box in Figure 6-6). The service rate at the exit gates is assumed to follow the Exponential distribution. The mean of Exponential distribution is also derived with regard to the extent of the workloads and the actual average of 3T. Figure 6-6 illustrates the departure module created in ARENA.



Figure 6-6: Departure module in ARENA

6.2.7 Terminal performance factors

In each phase of the simulation, from the existing condition (base case scenario) to the proposed plan (appointment scenario), the following factors are estimated to measure the effectiveness of different scenarios in handling trucks (e.g. demand and supply size).

- 1. Delay at the pre-gates and gates
- 2. Queue length at the pre-gates and gates
- 3. Delay at the truck interchange area

- 4. Transfer equipment utilization factor
- 5. Truck turn time

In this study, the period of time that trucks are waiting behind the pre-gates and gates, is also considered since the study has claimed that the proposed plan can reduce the queues behind the pre-gates and gates. Therefore, the truck turn time is estimated by

$$Tt = w_{pg} + w_g + w_{int} + w_e + T_g + T_{int} + T_e$$
 Equation 6-1

Where,

Tt = Truck turn time,

 w_{pg} = Truck waiting and service time at the pre-gate,

 w_g = Truck waiting and service time at the entrance gate,

- w_{int} = Truck waiting and service time at the truck interchange area,
- w_e = Truck waiting and service time at the exit gate,

 T_g = Travel time between the pre-gate and the entrance gate,

 T_{int} = Travel time between the gate and the truck interchange area,

 T_e = Travel time between the truck interchange area and the exit gate.

These critical factors are utilized to measure the gate and the truck interchange performance for the base case and the proposed scenarios. After the implementation of the appointment system at gates and the interchange area, the terminal performance factors are examined to validate the effectiveness of the proposed appointment system in improving truck services at the terminal. The overall time dedicated to the container handling at the entrance gates, the interchange area, and the exit gates along the routes' travel times in the simulation model are compared with the actual 3T to calibrate the service rate at the abovementioned locations. Since the 3T for the terminal being studied is not available, the average truck turn time extracted from the neighborhood terminal with the same characteristics (container terminal) is considered. Figure 6-7 depicts the 3T for one week of gate activities obtained from the actual data. As demonstrated, 40 minutes could be an appropriate assumption for the 3T assuming that no queue has been formed at the entrance gates in the beginning.



Figure 6-7: Truck turn time observation

Also, the number of inbound and outbound trucks created in the simulation model in different time periods (e.g. one hour and 30 days) is compared with the actual truck volumes in the same time period to investigate the fitness of the distribution mean of the arrival rate.

The calibration of the simulation model would be absolutely vital to build any practical model since any proposed scenarios will be built on the realistic conditions without any doubt of the credibility of the base case scenario.

6.3 Simulation Case Studies

Two major scenarios, existing (base case) and proposed (application of an appointment system), are implemented, evaluated, and compared to determine the performance of each scenario. Also, different conditions in each scenario are investigated to justify the appointment system in different conditions.

6.3.1 Base case scenario

Based on the designed model, the simulation model is built as a base case scenario and calibrated under the actual truck traffic and container volumes at the apron. The model runs for 30 days with ten days of warm up to provide enough containers at the yard for processing. In this model, the containers generated at the apron are handled completely by truck at the gates (other modes of transportation are not considered). Also, the evaluation of the actual data is revealed that some trucks arrive at the terminal to just pickup empty containers delivered at the terminal by vessels or trucks earlier and no connections can be drawn between gates and aprons in a near time period (the period of study). Although this volume is eliminated from the analysis in the analytical approach, this traffic is considered in the simulation phase since this volume affects the operation at gates, interchange area, and transfer equipments as well. Consequently, gate truck traffic is slightly higher than container volume at the apron. The truck turn time is set at about 40 minutes based on the actual data, although thirty minutes of 3T is assigned as an ideal

condition to achieve. Some literature also placed thirty minutes of 3T as a threshold for their simulation model (Sgouridis et al 2002, 2003). After training the model under real conditions, trucks and vessels are created based on the distribution function obtained from the actual data. As shown in Table 6-1, two first rows demonstrate the same conditions, the calibrated base case under real truck and vessel volumes (Actual Model) and under distribution volume (Distribution Model). Since the distribution model demonstrates the goodness of trained model, this model is utilized to implement the following scenarios on the base case. In each scenario, the terminal performance factors described in Subsection 6.2.7 are estimated to examine the terminal throughputs in different circumstances.

6.3.1.1 Sensitivity analysis

Scenario 1: Increasing truck volume at the terminal gates

In this case, the truck volume is increased by 20%. As shown in Table 6-1, the truck turn time is increased significantly as a consequence of delays at the pre-gates and gates. This circumstance shows clearly that gates would be the first bottleneck when we are close to the congestion state. The delay at the interchange area, however, has not increased, since we have an adequate number of spaces in the interchange area to manage the growing volume.

Scenario 2: Increasing import containers

In this scenario, import volumes are increased by 20%. As previously provided, there is a relationship between the apron and gates activities. The outcomes demonstrate that delays at the interchange area are increased slightly as a result of increasing TEs' jobs. Intuitively, the truck turn time is increased slightly because of the equipment shortages.

The validation of this interpretation is examined extensively under the following scenarios (3 & 4).

Scenario 3 and 4: Increasing import containers along decreasing TEs

Having Scenario 2 in place, a number of TEs are decreased by 10% (Scenario 3) and by 30% (Scenario 4). In Scenario 3, the terminal performance factors have not changed significantly from the previous condition. Scenario 4, however, shows that a greater reduction in the number of TEs would affect the terminal performance factors drastically. These scenarios emphasize the important fact that changing TEs' quantity at a terminal does not always affect the terminal performance factors. The accurate estimation of the number of TE depends on a good understanding of terminal conditions in any given time and conditions. As Saanen (2003, 2000) stated in his studies, increasing the number of equipment from a certain point not only would not increase, but also could decrease the productivity due to the blockage on the roadway inside ports.

Scenario 5: Increasing the volume of truck and containers carried by vessel

In this scenario, a number of containers carried by truck and vessel are increased by 20%. As expected, the truck turn time is increased significantly as a consequence of increasing delay at the pre-gates, gates and interchange area. This condition depicts well the intensity of workloads at the terminal. In this condition, it is evident that some policy-making decisions have to be performed to improve these conditions.

Scenario 6: Increasing truck volume and decreasing dwell time

In this scenario the truck volume is increased by 20% and the dwell time is reduced by one day. The results show that decreasing dwell time by one day also intensifies activities at gates. Upon combining these two conditions (increasing truck volume & decreasing CDT), delays at gates and pre-gates are higher by 15% as compared to Scenario one. As a result, the truck turn time is increased by 12%. By establishing a relationship between Scenario 6 findings and the first task outcomes, port operators would be able to observe how changing one of the CDT determinant factors such as ocean carrier (task one) can affect the CDT and consequently affect truck gate traffic.

Table 6-1: The terminal performance factors and different scenarios built over the base case

Scenario	Truck Turn time (Min)	Avg. Queue at pre-gates	Avg. Delay at pre-gate (Min)	Avg. Queue at gate	Avg. Delay at gate (Min)	Avg. Delay at interchange (Min)	Avg. Straddle carrier utilization factor	Number of trucks	Number of containers carried by vessel
Base case (Actual model)	37	0.57	2	0.17	1.2	11	0.27	44558	33758
Base case (Distribution model)	38	0.78	2.4	0.18	1.1	11	0.31	43812	33877
Scenario 1: Increasing truck volume by 20 percent	65	6	16	1	6	11	0.33	53291	33493
Scenario 2 : Increasing import containers by 20 percent	43	1	2.3	0.2	2	14	0.33	43689	40418
Scenario 3 : Increasing import containers by 20 percent and decreasing the number of straddle by 10 percent	43	1	2.3	0.3	2	15	0.43	43689	40418
Scenario 4 : Increasing import containers by 20 percent and decreasing the number of straddle by 30 percent	208	1	2.7	0.4	2.4	233	0.55	43743	40840
Scenario 5: Increasing truck and vessel volume by 20 percent	71	8	20	0.9	6	14	0.36	52604	40396
Scenario 6: Increasing truck volume by 20 percent and decreasing dwell time by one day	74	7	19.4	1.2	6	12	0.35	55593	33834
6.3.2 Appointment System- Proposed Plan and Design

By assuming that the appointment system is in place, two kinds of trucks are expected to arrive at the gates: trucks with the random arrival (Tr), and Trucks with an appointment (Ta). The serving of "Ta" at the pre-gates and gates is expected to have less complication and less variation, because the container, driver, and documents are cleared prior to the truck's arrival. In the appointment scenario-base case, the interchange area is divided into two groups; handling "Tr" and handling "Ta". The "Ta" has priority to get the Transfer Equipment (TE) services over "Tr". Figure 6-8 demonstrates the procedure of container's handling at the pre-gates, gates and interchange area by establishing the appointment system.



Figure 6-8: The schematic representation of the appointment system

To simulate the appointment system, the operating hours are divided into t hour time zones. A limited number of trucks are assigned per each time to handle containers efficiently at the gates, pre-gates, and interchange area. One approach could be the dedication of one interchange space to trucks with the appointment entering via the appointment gate and pre-gate. Since service rates are varied at these service sites, a minimum number of trucks can be considered to prevent the overcrowding; as shown in the following equation.

$$n = Min \{ t/S_{int}, t/S_g, t/S_{pg} \}$$
Equation 6-2

Where,

n = A number of "Ta" per t (= 1 hour = 60 minutes) time for one service site (pregate, gate or interchange area)

 S_{int} = Truck service rate per 1 TEU at the truck interchange area (t),

 S_{g} = Truck service rate per 1 TEU at the entrance gate (t), and

 S_{pg} = Truck service rate per 1 TEU at the pre-gate (t).

While this technique might prevent congestion at the interchange area, it increases the idle time in the gates where their service rates are lower. Based on the outcome obtained from the base case scenario and practices, truck processing at the interchange area requires extra time in comparison to the gate and pre-gate services. Therefore, more truck interchange spaces have to be assigned to each pre-gate and gate (dedicated to the appointment system). The following calculation is employed to determine a number of truck interchange areas to each entrance gate (Pre-gate & gate).

$$\begin{split} &I\alpha_{s0}(t) = P\alpha_{s0}(t - \epsilon_0) + S_{pg} + T_g + S_g + T_{int} \qquad \epsilon_0 > 0 \ \& \ t - \epsilon_0 > 0 \\ &I\alpha_{e0}(t + \epsilon_1) = S_{int} + I\alpha_{s0}(t) \\ &I\alpha_{s1} \ (t + \epsilon_2) \ge I\alpha_{e0}(t + \epsilon_1) \qquad \epsilon_2 > \epsilon_1 \end{split}$$
 Equation 6-3

Where,

 $I\alpha_{s0}$ = Time (t) that "Ta" truck *s0* arrive at the truck interchange area,

 $I\alpha_{s1}$ = Time (t+ ε_2) that "Ta" truck *s1* arrive at the truck interchange area,

 $P\alpha_{s0}$ = Time (t- ε_0) that "Ta" truck *s0* arrives at the pre-gate,

 S_{pg} = Truck service rate per 1 TEU at the pre-gate,

 T_g = Travel time between the pre-gate and the entrance gate,

 S_g = Truck service rate per 1 TEU at the entrance gate,

 $T_{int} = Travel time between the gate and the truck interchange area,$

 S_{int} = Truck service rate per 1 TEU at the truck interchange area, and

 $I\alpha_{e0} = Time (t-\varepsilon_1)$ that Ta truck *s0* departs the truck interchange area,

Equation 6-3 shows that the time that a truck with the appointment arrives at the truck interchange area can be estimated from the addition of the pre-gate service time, gate service time, travel time between pre-gate and gate, and travel time between gate and the truck interchange area to the time when truck arrives at the pre-gates $(t-\varepsilon_0)$. Thus, the time completion of the truck handling at the truck interchange area $(t+\varepsilon_1)$ has to be an equal or lesser than a next truck arrival time at the truck interchange area $(t+\varepsilon_2)$ to not have any queue at the truck interchange area.

In the following, an appointment system is established by assigning a defined number of trucks at the pre-gates, gates, and interchange spaces per time unit (hour) utilizing the above calculation.

6.3.2.1 Appointment System – Implementation Procedure

The proposed plan (the appointment system) dedicates certain lanes in entrance gates (pre-gates, truck interchange) to trucks that are making appointments and thus implies a certain service quality. The average processing time in these locations is derived from the base case scenario and utilized to calculate the appropriate number of trucks per time unit (hour). Equation 6-3 is applied manually for a few iterations. The outcomes revealed that three interchange slots per gate/ pre-gate with an average of 15 "Ta"- truck with the appointment (Equation 6-2: 60/4 [including 1 minute of extra time] = 15) per hour would be a good approximation in order to have no queues at those locations. The uniform distribution with a minimum of 15 and maximum of 16 per hour is assigned to the arrival of trucks with appointments for the period of 16 hours in weekdays (Monday through Friday) and 8 hours on Saturday.

The appointment system is implemented considering the above scenario along with some changes in the pre-gate and gate processing time. Flat rates of one and two minutes are assigned to the truck service rates at the pre-gate and entrance gate accordingly since trucks with the appointment expect to have less complication.

The comparison between the base case scenario in Table 6-1 and the appointment system scenario (Table 6-2 and Table 6-3) depicts that the truck turn time for the "Tr" (trucks with random arrival) has not changed significantly since some trucks divert their

businesses to the appointment system. About 10% of the total truck volume participating in the appointment system achieves the lowest truck turn time rate (= 23 Min.). This result demonstrates the effectiveness of the appointment system in elevating terminal throughputs.

In the following section, different scenarios are examined to investigate the robustness of the proposed system under various circumstances, such as increasing trucks with the appointment, trucks with random arrival, transfer equipments, and changing the schedule of trucks with the appointment ("Ta").

6.3.2.2 Sensitivity analysis

Scenario 1: Increasing the number of random trucks

Considering the existence of the appointment system at the pre-gate and gate, the number of "Tr" are increased to examine at what point the gates dedicated to the "Tr" are not capable of providing reasonable services. As illustrated in Table 6-2, the increase of trucks with random arrival by 20% increases truck turn time by 87%, while the appointment system provides an acceptable level of truck services for "Ta"s presented in Table 6-3.

Scenario 2 and 3: Increasing the number of random and appointment trucks

In this scenario, a number of "Tr" are increased by 20% and a number of "Ta" are increased by 20% (Scenario 2) and 85% (Scenario 3). These scenarios attempt to investigate the overall terminal performance and find an acceptable level of truck services for "Ta" considering the existing conditions (one pre-gate and gate and three interchange locations). Considering the ideal truck turn time (=30 minutes), the increase of "Ta" by

20% changes appointment trucks processing time slightly. As explained before, the study performed the conservative estimation to dedicate a defined number of "Ta"s per time slot and establish the priority system at the truck interchange area. Therefore, it is expected that the small increase in a number of "Ta"s would not change truck turn time significantly. The increase of "Ta" is performed for different rates (1.4, 1.5, 1.7, 1.85 and 2) to find out when the appointment system cannot present an acceptable condition. The increase of "Ta"'s volume by 1.4, 1.5 and 1.7 presents the effectiveness of the existing conditions (truck turn time <= 30 minutes) although the increase of trucks by the rate of 1.85 and 2 demonstrates an inefficiency of the appointment system under these circumstances. As scenario 3 in Table 6-3 shows, the truck turn time is worse (> 30 minutes) and increase by 87% due to the increase of delays at the gates. The delay at the interchange area has not changed due to the establishment of the priority system at the truck interchange for the benefit of "Ta"s.

Scenario 4: Increasing the number of random and appointment trucks along with decreasing the number of Transfer Equipments (TEs)

This scenario clearly shows the relationship between demand level (truck volume) and supply size (the number of TEs) on the terminal performance factors. Reducing the number of TEs (supply) by 30% along with increasing truck volume by 20% (demand) demonstrate that the "Tr" turn time deteriorated drastically (by 580% comparing with the Scenario 1), mainly as a consequence of increasing delays at the truck interchange area. The "Ta" trucks turn time changes slightly since the establishment of the priority system at the interchange area mandates service priority to the "Ta"s over "Tr"s.

Scenario 5: Increasing the number of trucks and decreasing the CDT

In this case, the number of trucks ("Ta" and "Tr") is increased by 20% and the CDT average is decreased by two days. As shown in Table 6-2 and Table 6-3, the truck turn time has not changed for "Ta"s although the overcrowding of "Tr"s to pick up their containers puts more pressure on pre-gates and increases the delay at this bottleneck (the increase of 84%).

Scenario 6: Appointment system with scheduling

In this scenario, an appointment system is established during the higher volume hours of the terminal's operations (6 AM to 6 PM) Monday through Friday. After those hours (6PM- 10PM) on weekdays and all day on weekends, no appointment system is in place and the terminal operates under typical arrival conditions (random). In these hours, trucks with random arrivals, called "evening trucks", are assigned to the pre-gate, gate, and truck interchange area dedicated previously to the appointment system. Clearly the "evening truck" has less truck turn time than "Tr" (25 Min. compared with 41 Min.), since the terminal is in the slack period, as shown in Table 6-3.

The result of the comparison between the base case appointment and this scenario shows that no significant difference can be distinguished. To examine the effectiveness of this scenario in different conditions, three following scenarios are developed.

Scenario 6.1, 6.2, and 6.3: Appointment system with scheduling and different levels of overall truck volume

These scenarios examine whether the increase of truck volume ("Tr" and "Ta") justifies the applicability and effectiveness of Scenario 6 since this scenario seems to present a more practical approach to the implementation of the appointment system. Scenario 6.1 increases the overall truck volume (random, evening, and appointment) by 20%. Scenario 6.2 increases by 50%. Finally, Scenario 6.3 increases "Tr" by 20%, "Ta" and "evening truck" by 70%. By comparing the results of Scenario 6.1 with Scenario 2, the outcomes revealed that Scenario 6.1 performs better than Scenario 2, even by handling more trucks in the period of the study. Scenario 6.2 definitely shows the inefficiency of the pre-gates (146 min. delay) in handling the "Tr"s, although entrance gates in the evening hours function much better (41 Min. for truck turn time). In this scenario, "Ta" achieves an acceptable level of performance (30 Min.). After the comparison between the outcomes of Scenario 6.3 and 2, Scenario 6.3 presents a marginal but an acceptable level of service for "Ta"s (truck turn time = 33 Min.), similar results as Scenario 2 for "Tr"s (truck turn time \approx 74 Min.), and much better results for evening trucks (truck turn time = 56 Min.). However Scenario 6.3 accepts much more truck volumes than scenario 2. Also the comparison of results between Scenario 6.3 and Scenario 1 in Table 6-1 demonstrates that the former provides much better services to trucks in evening and appointment, while providing comparable results for trucks with random arrivals, in spite of handling more trucks than Scenario 1. As shown in these two comparisons, Scenario 6.3 attempts to investigate the terminal throughputs when port operators establish an appointment system at gates in the peak hours and promote the usage of evening hours through particular policies (such as the establishment of congestion pricing at gates during the peak hours).

Table 6-2: The terminal performance factors for trucks with random arrivals in the appointment scenario

			Truck	s with random a	rrival				
Scenario	Truck Turn time for random arrival (Min)	Avg. Queue at pre-gates	Avg. Delay at pre-gate (Min)	Avg. Queue at gate	Avg. Delay at gate(Min)	Avg. Delay at interchange (Min)	Avg. Straddle carrier utilization factor	Number of Random trucks	Number of containers carried by vessel
Appointment- Base case scenario	41	3	8	0.2	1.20	12	0.3	39961	33831
Scenario1 : Increasing the number of random trucks by 20 percent	77	16	41	1	2	12	0.32	44161	33595
Scenario2 : Increasing the number of random trucks and appointment by 20 percent	75	16	40	1	2	12	0.31	44882.00	33815
Scenario3 : Increasing the number of random trucks by 20 and appointment by 85 percent	79	16	41	0.3	2	12	0.35	44547.00	33723
Scenario4 : Increasing the number of random trucks and appointments by 20 percent and decreasing TE by 30 percent	280	17	41	0.4	2	236	0.6	44370.00	34119
Scenario5 : Increasing the number of random trucks and appointments by 20 percent and decreasing CDT by two days (logN (1.76,0.5))	81	17	42	0.3	2	13	0.35	44505	33840
Scenario 6: Appointment with scheduling	39	3	9	0.2	1	11	0.3	38691	33411

Scenario 6.1: Scenario 6 with 20 percent increase of evening, appointment, and random trucks	76	15	35	0.3	2	12	0.3	46529	33411
Scenario 6.2: Scenario 6 with 50 percent increase of evening, appointment, and random trucks	203	77	146	0.6	3	14	0.33	58520	33353
Scenario 6.3: Scenario 6 with 70 percent increase of evening and appointment, and 20 percent increase of random trucks	74	16	37	0.3	2	11	0.3	46693	33466

Table 6-3: The terminal performance factors for trucks with the appointment in the appointment scenario

	Trucks with the appointment												
Scenario	Truck Turn time for appointme nt trucks (Min)	Truck Turn time for evening trucks (Min)	Avg. Appointment truck Queue at pre-gates	Avg. Appointment truck delay at pre-gates	Avg. Appointment truck Queue at gates	Avg. Appointment truck delay at gates	Avg. Delay at the appointment interchange (Min)	Number of Appointment	Number of evening trucks				
Appointment- Base case scenario	23		0	0.2	0.12	1	10	3951					
Scenario1 : Increasing the number of random trucks by 20 percent	23		0	0.2	0.11	1	10	3883					
Scenario2 : Increasing the number of random													
trucks and appointments by 20 percent	24		0	0.2	0.3	2	10	4833					
Scenario3 : Increasing the number of random trucks by 20 and													
appointments by 85 percent	43		0.12	1	5	21	11	7425					

Scenario4 : Increasing the number of random trucks and									
appointments by 20									
percent and decreasing			_			_			
TE by 30 percent	25		0	0.2	0.3	2	11	4812	
Scenario5 : Increasing									
the number of random									
trucks and									
appointments by 20									
percent and decreasing									
CDT mean by one day									
but the standard									
division by two days	27		0	0.2	0.2	2	11	4700	
(logn (1.76,0.5))	27		0	0.2	0.2	2	11	4780	
Scenario 6:									
Appointment with	22	25	0	0.2	0.2	2	10	2500	4 4 7 7
scheduling	23	25	0	0.2	0.2	2	10	2599	1477
Scenario 6.1: Scenario 6									
with 20 percent									
increase of evening,									
appointment, and	24	21	0	0.2	1	4	10	2127	1700
	24	31	0	0.3	1	4	10	3137	1783
Scenario 6.2: Scenario 6									
with 50 percent									
increase of evening,									
appointment, and	20	41	0.1	1	1	12	10	2022	2157
	50	41	0.1	1	1	12	10	3933	2157
with 70 percent									
increase of evening and									
annointment and 20									
nercent increase of									
random trucks	33	56	0.1	1	4.4	18	11	4433	2446
random trucks	33	56	0.1	1	4.4	18	11	4433	2446

6.4 Conclusion

This chapter developed a simulation model at the macro level to examine the robustness of the mathematical approaches built in the previous tasks and demonstrate the merit of this study in practices. The base case was designed based on a typical operation of container handling in marine terminals; the model was calibrated using the terminal data; different scenarios including the appointment system were developed; in each scenario, terminal performance factors were evaluated to probe the most practical and efficient solution easing congestion in different circumstances. The scenarios were developed based on different demands (increasing truck volume at the gates and container volume at the apron), different supply (decreasing transfer equipment), different container dwell time, and different appointment system scheduling. The results revealed that increasing truck volume and container volume at the apron could affect the terminal performance factors particularly in some conditions. The investigation on the effect of CDT changes on the terminal performance showed that decreasing CDT could increase truck turn time. Though, it might be obvious that the CDT affects the capacity of the terminal yard, no study has been found to examine the effect of the CDT changes on the terminal's gate traffic. These simulation scenarios presented that this factor has to be considered when the gate congestion relief strategies are under investigation.

The establishment of the appointment system was also performed and different scenarios under different circumstances were implemented. The outcomes revealed that the appointment system would be an effective system in servicing trucks at the entrance gates and inside the terminal, if the terminal had relatively medium to high truck traffic volume. The development of the appointment system in peak-hour and promoting the usage of evening hours through particular policies (such as the establishment of congestion pricing at gates during peak-hour) demonstrated that this scenario provided relatively an acceptable level of services by servicing more trucks in a defined time period. Clearly more studies are required to support this initiative.

It is worth to mention that the dissertation limits the establishment of the appointment system to entrance gates and the truck interchange area. The future study can provide a more comprehensive approach by looking at the hinterland highway network dedicating specific highway lane(s) to trucks with the appointments. It is expected that this tactic can provide more seamless environment for trucks with the appointment.

Chapter 7 CONCLUSION AND FUTURE RESEARCH

7.1 Conclusion

The dissertation provided evidences that there is a relationship between truck traffic at the gates and the apron container's volume at a marine container terminal. To establish this connection, the dissertation developed two approaches: analytical and simulation techniques. The analytical phase defined attributes affecting this relationship and developed models to draw this connection. The simulation phase examined this interrelationship in a virtual environment. The following findings are extracted from the implementation of these two approaches:

- The container dwell time was utilized to probe the terminal's throughputs and discern some basics that can be employed to measure the terminal performance. Although the current research has shown little interest in this topic, this dissertation has provided initial research on this principal factor (CDT).
- The container dwell time was estimated and predicted using determinant factors varying from supply chain participants to the physical location of a terminal and seasonal characteristics of the goods.
- The dissertation provided an analytical observation on the effect of the CDT determinant factors on the CDT. Similar findings could be extracted from any datasets in any container terminal.
- Any changes in the CDT determinant factors could affect the CDT, influencing yard capacity and the revenue earned from the demurrage fee.

- The CDT established the link between the truck gate traffic and the apron activities.
- Truck gate volumes could be estimated on a daily and hourly basis using the CDT distribution pattern based on the apron's volume.
- Scenarios developed in the simulation model revealed clearly that the CDT could affect truck traffic at gates.
- The establishment of an appointment system at truck gates developed in the simulation environment confirmed that this system could improve the terminal performance factors significantly. The efficiency of this system was also investigated and confirmed when the appointment system was only initiated during the terminal's intense work hours.

7.2 Recommendations for future research

The author believes that the dissertation only looked at the tip of the iceberg in some areas and more exhaustive research is needed to extend the current work. The following recommendations are made for the extension of the current work:

7.2.1 Analytical related recommendations

• *Expansion of CDT modeling* - The CDT estimation methodology can be extended to more than one terminal. Terminals can be chosen from a variety of regional, local, and transshipment hubs. The developed framework can be utilized on the datasets and significant factors of CDT determinants can be derived to predict CDT for each terminal. In addition, obtaining the shippers' and consignees' information could improve the CDT prediction.

- *Exhaustive economic assessment* Many parameters have not been considered in calculating terminal revenue using the CDT. An elaborate economic analysis should be provided to assess the benefit and cost associated with the CDT changes. The tradeoff between truck gate congestion and air pollution (as cons), on one hand, and the capacity gained and fewer reshuffling movements (as pros), on the other hand, can be mentioned as one paradigm.
- *Rail Study* The study sets aside the rail yard operations from the calculation. The same examination on the effective factors on the CDT can be performed for rail traffic. Also the same relation between the apron's activities and the rail yard can be drawn using the model developed for the truck gates.

7.2.2 Policy related recommendations

- *Free time evaluation* Exploring the most suitable free time period can be an interesting research for port operators who are constantly looking for cost-effective solutions.
- *Appointment system economic analysis* Although, the establishment of the appointment system improves terminal performance, saves truck productive time, and decreases air pollution, it obviously imposes some expenses on the terminal operators such as developing the software, maintaining the application, dedicating the specific gates for the appointment trucks, and the labor costs. Apparently, more extensive studies have to be performed to justify the implementation of this system at all times or the particular time period (e.g. the intensive terminal work hours).

- *Hinterland terminal congestion assessment* The simulation model can extend the study area and go beyond the gate bottlenecks, analyzing the congestion in the hinterland roadway network with and without the appointment system. This evaluation would be interesting research for transportation agencies exploring solutions to mitigate the congestion around marine terminals.
- *Technology usage* The simulation model can be extended to the operational level. Practitioners can evaluate the effect of state of the art technologies on the gate traffic and compare the results with the establishment of an appointment system at the gates.

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APPENDIXES

Appendix 1a: Vessel classification

```
Sub classify()
Dim vesselcount, i As Integer
i = 2
For i = 2 To 128
  vesselcount = Worksheets("VesselIBTOBS2Jan").Cells(i, 1).Value
  Select Case vesselcount
  Case 1 To 299
    Worksheets("VesselIBTOBS2Jan").Cells(i, 3).Value = 1
  Case 300 To 599
    Worksheets("VesselIBTOBS2Jan").Cells(i, 3).Value = 2
  Case 600 To 999
    Worksheets("VesselIBTOBS2Jan").Cells(i, 3).Value = 3
  Case 1000 To 1399
    Worksheets("VesselIBTOBS2Jan").Cells(i, 3).Value = 4
  Case 1400 To 1799
    Worksheets("VesselIBTOBS2Jan").Cells(i, 3).Value = 5
  Case 1800 To 2199
    Worksheets("VesselIBTOBS2Jan").Cells(i, 3).Value = 6
  Case 2200 To 2599
    Worksheets("VesselIBTOBS2Jan").Cells(i, 3).Value = 7
  Case 2600 To 2999
    Worksheets("VesselIBTOBS2Jan").Cells(i, 3).Value = 8
  Case 3000 To 3499
    Worksheets("VesselIBTOBS2Jan").Cells(i, 3).Value = 9
  Case 3500 To 4000
    Worksheets("VesselIBTOBS2Jan").Cells(i, 3).Value = 10
  End Select
Next i
End Sub
```

Appendix 1b: Truck classification

```
Sub classify()
Dim Truckcount, i As Integer
i = 2
For i = 2 To 719
  Truckcount = Worksheets("TruckOBTIBSJan").Cells(i, 1).Value
  Select Case Truckcount
  Case 1 To 99
     Worksheets("TruckOBTIBSJan").Cells(i, 3).Value = 3
  Case 100 To 399
    Worksheets("TruckOBTIBSJan").Cells(i, 3).Value = 4
  Case 400 To 699
    Worksheets("TruckOBTIBSJan").Cells(i, 3).Value = 5
  Case 700 To 999
    Worksheets("TruckOBTIBSJan").Cells(i, 3).Value = 6
  Case 1000 To 1299
    Worksheets("TruckOBTIBSJan").Cells(i, 3).Value = 7
  Case 1300 To 1599
    Worksheets("TruckOBTIBSJan").Cells(i, 3).Value = 8
  Case 1600 To 1900
    Worksheets("TruckOBTIBSJan").Cells(i, 3).Value = 9
  Case 1901 To 2200
    Worksheets("TruckOBTIBSJan").Cells(i, 3).Value = 10
  Case 2201 To 2500
    Worksheets("TruckOBTIBSJan").Cells(i, 3).Value = 11
  Case 2501 To 2800
    Worksheets("TruckOBTIBSJan").Cells(i, 3).Value = 12
  Case 2801 To 3100
    Worksheets("TruckOBTIBSJan").Cells(i, 3).Value = 13
  Case 3101 To 3400
    Worksheets("TruckOBTIBSJan").Cells(i, 3).Value = 14
  End Select
Next i
End Sub
```

Appendix 2a: Attributes probability profile

		Population										
	States	(All)	D8	D9	D4	D5	D6	D7	D0	D1	D2	D3
Size		73657	6636	2861	8468	8655	7860	8830	4028	7696	9015	9608
IBTCOde2	118	15204	34 %	37 %	19 %	18 %	18 %	23 %	13 %	13 %	21 %	20 %
IBTCOde2	18	11673	22 %	14 %	14 %	16 %	15 %	20 %	18 %	16 %	11 %	14 %
IBTCOde2	122	8678	8 %	10 %	14 %	16 %	18 %	15 %	5 %	9 %	9 %	10 %
IBTCOde2	114	7165	4 %	4 %	10 %	10 %	9 %	5 %	23 %	19 %	10 %	7 %
IBTCOde2												
IBTWeeknumber	3	16071	32 %	28 %	19 %	15 %	27 %	22 %	19 %	24 %	19 %	19 %
IBTWeeknumber	2	14933	20 %	30 %	19 %	18 %	14 %	21 %	22 %	23 %	26 %	17 %
IBTWeeknumber	4	14806	14 %	14 %	21 %	27 %	23 %	23 %	16 %	16 %	21 %	19 %
IBTWeeknumber	6	14534	17 %	13 %	18 %	23 %	17 %	18 %	30 %	15 %	18 %	28 %
IBTWeeknumber	5	12874	17 %	14 %	22 %	18 %	18 %	16 %	13 %	22 %	15 %	17 %
IBTWeeknumber	7	439	0 %	2 %	1%	0 %	0 %	0 %	0 %	1%	1 %	1 %
LHTCode6	L26	25867	51 %	42 %	32 %	32 %	36 %	46 %	23 %	28 %	29 %	34 %
LHTCode6	L18	24099	29 %	31 %	36 %	40 %	36 %	31 %	23 %	29 %	31 %	34 %
LHTCode6	L5	16272	15 %	19 %	23 %	19 %	19 %	15 %	33 %	28 %	29 %	23 %
LHTCode6	L30	2516	2 %	3 %	5 %	4 %	4 %	4 %	3 %	3 %	3 %	3 %
LHTCode6	L34	1634	1 %	2 %	2 %	2 %	2 %	2 %	3 %	3 %	3 %	2 %
LHTCode6	L10	1122	0 %	0 %	0%	0 %	0 %	0 %	9 %	5 %	3 %	1 %
LHTCode6												
ObScode3	015	15208	34 %	37 %	19 %	18 %	18 %	23 %	13 %	13 %	21 %	20 %
ObScode3	07	14657	24 %	17 %	17 %	19 %	16 %	23 %	27 %	24 %	15 %	20 %

ObScode3	019	8678	8 %	10 %	14 %	16 %	18 %	15 %	5 %	9 %	9 %	10 %
ObScode3	013	7165	4 %	4 %	10 %	10 %	9 %	5 %	23 %	19 %	10 %	7 %
ObScode3	018	5914	5 %	7 %	8%	8 %	12 %	6 %	3 %	7 %	12 %	9 %
ObScode3								•••				
OBSWeeknumber	4	14804	29 %	17 %	13 %	25 %	25 %	27 %	26 %	29 %	16 %	0 %
OBSWeeknumber	6	11476	15 %	20 %	10 %	0 %	9 %	17 %	29 %	21 %	25 %	19 %
OBSWeeknumber	·3	9723	11 %	0 %	15 %	18 %	24 %	20 %	19 %	6 %	1 %	13 %
OBSWeeknumber	5	9715	20 %	30 %	0 %	9 %	15 %	16 %	10 %	18 %	17 %	8 %
OBSWeeknumber	·2	9599	0 %	8%	23 %	21 %	19 %	10 %	5 %	0 %	8 %	23 %
OBSWeeknumber	·7	9257	15 %	14 %	18 %	9 %	0 %	10 %	11 %	18 %	14 %	17 %
OBSWeeknumber	1	9083	9 %	11 %	22 %	18 %	8 %	0 %	0 %	7 %	19 %	19 %
Status2	S2	40519	80 %	61 %	60 %	67 %	71 %	76 %	18 %	22 %	36 %	48 %
Status2	S1	33138	20 %	39 %	40 %	33 %	29 %	24 %	82 %	78 %	64 %	52 %
Truck class8	TC4	26137	32 %	32 %	35 %	35 %	36 %	33 %	42 %	39 %	37 %	36 %
Truck class8	TC5	14648	20 %	22 %	19 %	21 %	20 %	20 %	18 %	20 %	20 %	20 %
Truck class8	TC6	6459	11 %	10 %	9%	10 %	10 %	11 %	6 %	6 %	7 %	8 %
Truck class8	тсз	5070	5 %	7 %	7 %	7 %	7 %	5 %	7 %	8 %	8 %	7 %
Truck class8	TC1	5034	6 %	6 %	7 %	6 %	6 %	6 %	8 %	8 %	8 %	8 %
Truck class8	TC9	4880	10 %	7 %	9%	9 %	8 %	9 %	0 %	1%	4 %	7 %
Truck class8	TC2	4343	4 %	6 %	6%	5 %	5 %	5 %	8 %	8 %	7 %	6 %
Truck class8	TC8	3698	10 %	8%	3 %	3 %	5 %	8 %	4 %	4 %	5 %	4 %
Truck class8	ТС7	3388	2 %	3 %	5 %	3 %	3 %	3 %	8 %	8 %	6 %	6 %
Vesselclass7	VC4	33389	39 %	44 %	47 %	48 %	41 %	37 %	43 %	49 %	52 %	49 %
Vesselclass7	VC3	17186	15 %	22 %	30 %	27 %	26 %	19 %	25 %	20 %	20 %	27 %
Vesselclass7	VC5	11916	26 %	26 %	11 %	16 %	18 %	22 %	12 %	13 %	14 %	11 %
Vesselclass7	VC2	4358	7 %	6 %	7 %	4 %	6 %	8 %	1%	6 %	6 %	6 %
Vesselclass7	VC6	3310	9 %	1%	2 %	4 %	8 %	10 %	1%	2 %	1 %	3 %

Vesselclass7	VC7	1862	4 %	2 %	2 %	0 %	2 %	4 %	2 %	3 %	3 %	3 %
Vesselclass7	VC10	1599	0 %	0 %	0%	0 %	0 %	0 %	16 %	7 %	3 %	1 %
Vesselclass7	VC1	37	0 %	0 %	0%	0 %	0 %	0 %	1%	0 %	0 %	0 %
VesselCode5	Missing	6107	9 %	10 %	10 %	6 %	7 %	10 %	5 %	8 %	8 %	10 %
VesselCode5	V56	1862	4 %	2 %	2 %	0 %	2 %	4 %	2 %	3 %	3 %	3 %
VesselCode5	V83	1599	0 %	0 %	0%	0 %	0 %	0 %	16 %	7 %	3 %	1 %
VesselCode5	V37	1362	2 %	0 %	2 %	2 %	2 %	4 %	4 %	2 %	0 %	1%
VesselCode5	V29	1354	4 %	0 %	1%	2 %	3 %	4 %	1%	2 %	0 %	0 %
VesselCode5											•••	

Appendix 2b: Outcomes of C4.5 (ID3 successor algorithm) WEKA module on

sample of data

```
Code Vessel2 = V104
| IBT weekday <= 3
| | Status_code2 = S1: D0 (17.0/2.0)
| | Status_code2 = S2
| | | IBT_weekday <= 2: D8 (14.0/2.0)
1
  | | IBT weekday > 2: D7 (16.0)
| IBT_weekday > 3
| | IBT_weekday <= 5
| | | IBT_weekday <= 4: D6 (5.0/1.0)
| | | IBT_weekday > 4: D5 (20.0/2.0)
| | IBT_weekday > 5: D4 (24.0)
Code Vessel2 = V55
| IBT_weekday <= 4
| | IBT weekday <= 3: D3 (20.0/2.0)</p>
| | IBT_weekday > 3: D2 (83.0/1.0)
IBT_weekday > 4
| | Code LHT2 = L19
| | | Status_code2 = S1
| | | IBT_weekday <= 6: D0 (11.0)
| | | IBT_weekday > 6: D6 (3.0)
| | | Status_code2 = S2: D7 (10.0/1.0)
      a 1 11000
```


























Friday – Import by Vessel











Appendix 4: Hourly Pattern Import containers









Export containers – Hourly distribution

0.12

0.1

0.08

0.04 0.02

0

0.12

0.1

0.08

0.06

0.04

Density

0

Density 0.06 Histograms

10

Histograms

5

hourinbytruck





Cont'd: Export containers – Hourly distribution

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- Ph.D. in Civil Engineering May 2010, Rutgers, The state University of NJ
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Publications

- Moini, N., Boile, M., Laventhal, W., Theofanis, S., Developing a competing model to estimate the container dwell time using a set of determinants, Presented in 89th Transportation Research Board annual meeting, Washington DC, 2010.
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