MAXIMIZING CONTAINER TERMINAL THROUGHPUT BY INTERNAL TRACTORS ASSIGNMENT AND SCHEDULING

WANG ZHENGXU

Ph.D

The Hong Kong Polytechnic University

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The Hong Kong Polytechnic University

Department of Industrial and Systems Engineering

Maximizing Container Terminal Throughput by Internal Tractors Assignment and Scheduling

Wang Zhengxu

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CERTIFICATE OF ORIGINALITY

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WANG ZHENGXU (Name of student)

Abstract

Terminal operations are known to be among the most challenging operational research topics because the field is full of theories with applications to real-life practice. In the last decade, terminal operations research has been carried out on such topics as berth allocation, quay crane scheduling, yard planning, container locating and internal tractors assignment and scheduling (ITAS). The latter is a particularly important topic since it directly affects the overall performance of container terminals, involving terminal productivity, equipment utilization and service rate, as well as associated seaside operations with yard-side operations. It involves the scheduling of internal tractors to transport different loading and unloading containers between vessels at the quayside and the yard side. The idea of ITAS is to improve the internal traffic flow in the container terminal. It mainly deals with the problem of assigning different internal tractors to pick-and-drop different exporting containers from the yard side to the quayside, and importing containers from the quayside to the yard side.

However, many container terminal companies are still not able to efficiently and effectively cope with ITAS in the terminal logistic. There are a few challenging problems with respect to planning and managing a container transportation network

that trouble terminal operators in terminal industry. In fact, the experience of an operator plays a crucial role in making the decision for exact number of internal tractors and transportation routes in daily operations. This is due to that the number of containers and storage locations are so large that the job of assigning and scheduling internal tractors to maximize terminal efficiency and enhance service level is extremely complicated. Moreover, allocating suitable storage locations for inbound containers requires a jointly consideration of managing internal tractors. It is difficult to decide which storage locations should be reserved for a certain vessel and where an inbound container should be stored, and this situation becomes even more complicated when transhipment is required.

Although ITAS has been thoroughly researched, most of the studies lack consideration of practical issues, such as terminals outsourcing a number of internal tractors to perform a set of container delivery requests, and the transportation of transhipment containers. Due to a highly competitive business environment, container terminals are facing a tradeoff between container transportation efficiency and cost. Terminals strive to increase the efficiency of container delivery, which may need good transportation schedules and internal tractor deployment strategies. The scheduling and assignment of internal tractors is critical for maintaining high terminal performance in the overall container terminal system. In this connection, this study considers ITAS integration with the internal tractor deployment strategy and transhipment operations, and new models are developed. The ultimate goal is to maximize the terminal operation efficiency. Heuristic algorithms are proposed to solve these integrated and complicated models. Computational results show that solving the integration problem as a whole can significantly improve the terminal operation efficiency.

This research is not only pioneering in the area of container terminal operations, but the findings also provide a vital reference for future research on ITAS. The study has generated the following five deliverables: (i) ITAS is enriched by formulating and modeling all potential available storage locations; (ii) a novel ITAS system integrating container storage allocation and yard truck deployment strategy is identified and modeled; (iii) a two-level heuristic optimization methodology is developed to deal with the novel ITAS system, which is shown to obtain better results compared with other algorithms; (iv) a new ITAS system for transhipment container delivery and transportation in transhipment hubs is detailed demonstrated and modeled; and (v) a decomposition iterative algorithm optimization methodology for the proposed ITAS system in transhipment hubs is proposed.

List of Publications

International Journal Papers

Z.X. Wang, Felix T.S. Chan, S.H. Chung, Ben Niu, 2014. A decision support method for internal truck deployment. *Industrial Management and Data Systems*, 114(9), 1378-1395.

Z.X. Wang, Felix T.S. Chan, S. H. Chung, and Ben Niu, 2014. Minimization of delay and travel time of yard trucks in container terminals using an improved GA with guidance search. *Mathematical Problems in Engineering*. Article ID 710565, (Accepted In Press).

Z.X. Wang, Felix T.S. Chan, and S.H. Chung, 2015. A planning model for transhipment container transport and storage. *Computers and Operation Research*. (Under Review)

International Conference Papers

Z.X. Wang, Felix T.S. Chan, and S.H. Chung, Storage allocation and yard trucks scheduling in container terminals using a genetic algorithm approach, *The 3rd International Conference on Electrical, Computer, Electronics and Biomedical Engineering and The 3rd International Conference on Social Sciences, Management, Biotechnology and Environment Engineering (ICECEBE 2013)*, Singapore, April 29-30, 2013.

Z.X. Wang, Felix T.S. Chan, S.H. Chung, and Niu, B., An optimal strategy for yard trucks management in Hong Kong container terminals, *The 2013 International Symposium on Marketing, Logistics, and Business (MLB 2013)*, Nagoya, Japan, Sept 24-26, 2013.

Z.X. Wang, Felix T.S. Chan, S.H. Chung, and Niu, B. Yard truck configurations for efficient operation of container terminals in Hong Kong, *The 2014 International Conference on Information Science, Electronics and Electrical Engineering (ISEEE 2014)*, Sapporo City, Hokkaido, Japan, April 26-28, 2014.

Niu B., Xie T., Felix T.S. Chan, L.J. Tan, and **Z.X. Wang**. Particle swarm optimization for the truck scheduling in container terminals. *The 2014 International Conference on Information Science, Electronics and Electrical Engineering(ISEEE 2014)*, Sapporo City, Hokkaido, Japan, April 26-28, 2014.

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Table of Contents

List of Figures

List of Tables

List of Abbreviations

AGV	Automatic Guided Vehicle
ALV	Automatic Lifting Vehicle
BAP	Berth Allocation Problem
DIA	Decomposition Iterative Algorithm
DSS	Decision Support System
DTS	Direct Transfer System
FEU	Forty-foot-equivalent-unit
GA	Genetic Algorithm
IT	Internal Tractors
ITAS	Internal Tractors Assignment and Scheduling
ITS	Indirect Transfer System
MIP	Mixed Integer Programming
QC	Quay Crane
QCAP	Quay Crane Assignment Problem
QCSP	Quay Crane Scheduling Problem
RMGC	Rail-mounted Gantry Crane
RTGC	Rubber-tired Gantry Crane
SAP	Storage Allocation Problem
SC	Straddle Carrier
TEU	Twenty-foot-equivalent-unit
TLH	Two-level Heuristic
YC	Yard Crane
YCS	Yard Crane Scheduling
YGC	Yard Gantry Crane
YTS	Yard Truck Scheduling

Nomenclatures

Approach for YTS-SAP

i, j Index of request, $i \neq j$.

r Index of route.

p, q Index of location.

k Index of storage location.

$\tau_{p,q}$ Travel time between location p to location q.

o_i Origin of request i.

e_i Destination of request i.

ζ_k Location of storage location k.

α_1 Weighting of delay.

α_2 Weighting of travel time.

J^- Set of discharging requests with cardinality of $|J^-| = n^-$.

J^+ Set of loading requests with cardinality of $|J^+| = n^+$.

J Set of all requests, $J = J^- \cup J^+$, with cardinality of $|J| = n$.

J' Union set of all requests and initial status, $J' = J \cup \{l_r\}$

J'' Union set of all requests and final status, $J'' = J \cup \{k_r\}$.

R Set of routes, $|R| = \mathrm{m}$.

M Set of locations of the loading containers.

N Set of locations of the discharging containers.

K Set of the storage locations.

L Union set of the locations of the loading containers, the locations of the discharging containers and the storage locations. $L = M \cup N \cup K$.

x_{ik} = 1, if container i is allocated to storage location k.
= 0, otherwise.

y_{ij} = 1, if request i is connected to request j in the same route.

= 0, otherwise.

w_i Starting time of request i.

c_i Completion time of request i.

d_i Delay of request i.

t_i Processing time of the yard trucks from the origin of request i to the destination of request i. $t_i = \tau_{oi,ei}$, if request i is a loading request; $t_i = \tau_{oi,\zeta k}$, if request i is a discharging request and allocated to storage location k.

s_{ij} Setup time of the yard trucks from the destination of request i to the origin of request j. $s_{ij} = \tau_{ei,oj}$, if request i is a loading request; $s_{ij} = \tau_{\zeta k,oj}$, if request i is a discharging request and allocated to storage location k.

Approach for yard truck deployment strategy in gateway terminals

g, k Index of locations.

r Index of days.

i, j Index of containers.

R Set of days.

N_r Set of all containers on day r.

N_r^+ Set of import containers on day r.

N_r^- Set of export containers on day r.

N_r' Set of all containers and initial status.

N_r'' Set of all containers and finial status.

M_r Set of all available storage locations on day r.

a_i Earliest possible time of container i.

b_i Due time of container i.

w Processing time of quay cranes and yard cranes to process a container.

$\tau_{g,k}$ Travel time between each pair of locations (g, k).

o_i Origin of container i.

e_i Destination of export container i.

φ_{mr} Location of storage location m_r.

α_1 Cost of owning an internal truck.

α_2 Cost of using an owned yard truck per day.

α_3 Cost of using an rented yard truck per day.

α_4 Cost of delay per time unit.

p_i Processing time of export container i.

q_{ij} Setup time of two successive containers i and j, container i is an export container.

T_r Number of internal trucks employed on day r.

c_i Starting time of container i.

f_i Completion time of container i.

d_i Delay of container i.

p_i Processing time of import container i.

q_{ij} Setup time of two successive containers i and j, container i is an import container .

x_{imr} = 1, if container i is allocated to storage location m_r.
= 0, otherwise.

y_{ij} = 1, if container j is served immediately after container i by the same truck.
= 0, otherwise.

H Number of internal trucks owned by a container terminal.

S_r Number of internal trucks rented on day r by a container terminal.

H_r Number of owned internal trucks H_r used on day r by a container terminal.

Approach for storage space assignment in transhipment hubs

i, j Index of vessels.

k	Index of sub-blocks.
z	Index of container groups.
b	Index of berth segments.
V	Set of vessels.
B	Set of berth segments.
K	Set of sub-blocks.
GP	Set of groups.
BV	Maximum number of containers that a sub-block can store.
GN	Number of containers in a group.
$\mu_{z,i,j}$	= 1, denotes group z is located in vessel i and waiting for the transhipment from vessel i to vessel j; $\mu_{z,i,j}$= 0, otherwise; $i, j \in V$, $i \neq j$.
$D^U_{k,b}$	Length of unloading path between each pair of berth segment b and sub-block k; $k \in K$, $b \in B$.
$D^L_{k,b}$	Length of loading path between each pair of sub-block k and segment b; $k \in K$, $b \in B$.
$\varphi_{i,k}$	= 1, denotes vessel i has a reservation sub-block k; $\varphi_{i,k}$ = 0, otherwise; $i \in V$, $k \in K$.
$\omega_{i,b}$	= 1, denotes vessel i is berthed in berth segment b; $\omega_{i,b}$ = 0, otherwise; $i \in V$, $b \in B$.
$\psi^S_{z,b}$	Set to one if the starting position of group z is berthed in berth segment b, and zero otherwise; $z \in GP$, $b \in B$.
$\psi^E_{z,b}$	Set to one if the ending position of group z is berthed in berth segment b, and zero otherwise; $z \in GP$, $b \in B$.
M	Large positive number.
$x_{z,k}$	Set to one if group z is allocated to sub-block k, and zero otherwise; $z \in GP$, $k \in K$.

λ_z Processing distance of group z; $z \in GP$.

Approach for YTS-SAP in transhipment hubs

i, j Index of vessels.

k Index of sub-blocks.

z Index of container groups.

ca, cb Index of jobs.

b Index of berth segments.

V Set of vessels.

B Set of berth segments.

K Set of sub-blocks.

GP Set of groups.

BV Maximum number of containers that a sub block can store.

GN Number of containers in a group.

$\mu_{z,i,j}$ = 1, denotes group z is located in vessel i and waiting for the transhipment from vessel i to vessel j; $\mu_{z,i,j}$= 0, otherwise; $i, j \in V$, $i \neq j$.

TN Number of trucks.

ds Dummy start job.

de Dummy end job.

JA Set of loading jobs.

JB Set of unloading jobs.

JJ Set of loading and unloading jobs; $JJ = JA \cap JB$.

JS Set of loading, unloading jobs and the dummy start job; $JC = JJ \cap \{ds\}$.

JE Set of loading, unloading jobs and the dummy end job; $JC = JJ \cap \{de\}$.

$ld_{z,ca}$ = 1, denotes job ca is the loading job of group z; $ld_{z,ca}$= 0, otherwise; $z \in GP$, $ca \in JJ$.

$ud_{z,cb}$ =1, denotes job cb is the unloading job of group z; $ud_{z,cb}$= 0, otherwise; $z \in GP$, $ca \in JJ$.

$D^B_{b,b'}$ Length of traveling path between each pair of berth segment b and berth segment b'; b, $b' \in B$.

$D^K_{k,k'}$ Length of traveling path between each pair of sub-block k and sub-block k'; k, $k' \in K$.

$D^U_{k,b}$ Length of unloading path between each pair of berth segment b and sub-block k; $k \in K$, $b \in B$.

$D^L_{k,b}$ Length of loading path between each pair of sub-block k and segment b; $k \in K$, $b \in B$.

$\varphi_{i,k}$ = 1, denotes vessel i has a reservation sub-block k; $\varphi_{i,k}$ = 0, otherwise; $i \in V$, $k \in K$.

$\omega_{i,b}$ = 1, denotes vessel i is berthed in berth segment b; $\omega_{i,b}$ = 0, otherwise; $i \in V$, $b \in B$.

$\psi^S_{z,b}$ Set to one if the starting position of group z is berthed in berth segment b, and zero otherwise; $z \in GP$, $b \in B$.

$\psi^E_{z,b}$ Set to one if the ending position of group z is berthed in berth segment b, and zero otherwise; $z \in GP$, $b \in B$.

M A large positive number.

$x_{z,k}$ Set to one if group z is allocated to sub-block k, and zero otherwise; $z \in GP$, $k \in K$.

$y_{ca,cb}$ Set to one if job ca and cb are successive jobs and handled by the same truck, and zero otherwise; $ca \in JS$, $cb \in JE$.

$\tau_{ca,cb}$ The empty trip distance from job ca to job cb; $ca \in JJ$, $cb \in JJ$, $ca \neq cb$.

λ_z The processing distance of group z; $z \in GP$.

Chapter 1 Introduction

1.1 Problem Statement

Containers are standard-sized metal boxes that are used for transporting cargo by various kinds of transportation, such as sea-going vessels, trains, and trucks. Since the first regular sea container service about six decades ago, containerization has developed to the point where the throughput of containers worldwide is now more than 500 million twenty-foot-equivalent-units (TEUs) a year. Such a large number of containers need a considerable number of seaport container terminals to handle them. As a result, competition among container terminals has emerged so that they have to be competitive in order to attract customers and be profitable. A competitive terminal requires low port cargo handling charges, since a port with a lower charge is more competitive than its rivals (Tongzon and Heng, 2005). Companies managing container terminals are making an effort to cut costs so that they can offer competitive charges. A crucial competitive advantage is the rapid turnover of the containers, which corresponds to a reduction of the time in port of the container ships, and of the costs of the transhipment process itself (Steenken *et al*., 2004). Container terminals put a lot of effort into shortening the turnaround time by developing various decision support technologies to optimize terminal operations (Steenken *et al*., 2004). Generally, terminal operations contain berth allocation, quay crane scheduling, internal vehicle scheduling, yard crane scheduling and storage space allocation (Lee *et al*., 2009). All these operations are related to each other and an integral part of the terminal operations system that seeks to minimize the turnaround time of vessels. Collaboration in these operations creates an efficient and effective terminal operations system.

Inbound and transhipment containers are unloaded from a vessel by quay cranes (QCs). Internal vehicles deliver the unloading containers from the QCs to the storage yard where they are stacked by yard cranes (YCs) for temporary storage until they are transferred to another vessel or some transport mode inland. Alternatively, after a short storage time in the yard, outbound containers are delivered to internal vehicles by YCs and are transferred to QCs, which pick up the containers from internal vehicles and load them onto the vessel.

Several research problems must be solved before an efficient and effective terminal operations system is established. The first problem is scheduling internal vehicles to perform a number of transportation jobs and finding suitable storage space for inbound containers. There is a strong relationship between the storage allocation of containers and the dispatching of internal vehicles. It is known that the location of the stored containers directly affects the distance and time required by internal vehicles for transportation and consequently the terminal throughput (Bish *et al.*, 2001 and Bish, 2003).

Some container terminals can deploy internal vehicles using different approaches, i.e. rent vehicles from an outsourcing company or purchase all vehicles for their own use. As demand fluctuation is common in terminal industries, keeping a full fleet of trucks to meet all the internal transportation requirements is not economical (Petering, 2011). In addition, employing a large number of trucks not only costs extra money, but may also result in traffic congestion (Angeloudis and Bell, 2010). Moreover, the deployment cost of vehicles is different, and the number of vehicles influences the vehicle dispatching policy and efficiency for moving containers. Resolving the balance between terminal productivity and efficiency is another important task.

Transhipment at container terminals means that a number of containers are handled at the port and, after temporary storage in the yard, are transferred to another vessel. The transhipment of containers is a major activity for large container terminals, such as the Ports of Singapore, Hong Kong, etc. The storage locations of transhipment containers should be convenient for both unloading from the arriving vessel and loading to the departing vessel. This distinguishes the storage from inbound containers, since the inbound containers have no departing vessel to be considered. Thus, the allocation of storage locations for temporary storage of transhipment containers is a critical problem for terminals.

The transhipment operation in container terminals is complicated, which is not only related to the transport operation, but is also related to the seaside and yard-side operations. Accordingly, delivering the transhipment containers with full consideration of the terminal operations, e.g. internal vehicle routing, berth allocation, yard crane assignment and storage allocation, is an ultimate goal.

This study seeks to develop mathematical models and propose solutions for the abovementioned problems. To assist terminal operators, the transportation of inbound, outbound and transhipment containers are studied, considering the fiscal and managerial policies, as well as operating strategies.

1.2 Contribution of this Research

1.2.1 Limitations of Existing Studies

Previous studies considered the dispatching rules of ITs either with a fixed number of ITs, or by disregarding terminal system operations. This research, however, studied ITAS with variable numbers of ITs, and integrated storage allocation, which directly affects the routing of ITs. Since the strategy of dispatching ITs is related to other operations in the terminal, a study of this issue will significantly contribute to terminal operation systems.

Previous studies assumed that terminals have a full set of ITs, which are always available to transport containers. However, some terminals prefer to outsource ITs to help them meet transportation requirements, since outsourcing ITs is convenient and flexible; such is the case in the Port of Hong Kong. Consideration of both owned and outsourced ITs can also contribute to terminal business in a practical sense by introducing new insights to terminal managers.

Studies of ITs assignment and scheduling in the existing literature always consider the problem in a single time horizon, e.g. one day. However, the number of ITs employed each day should be related to the fluctuation of the terminal throughput in order to achieve long-term beneficial optimization, fulfillment of which is also a significant contribution to the operation of container terminals.

In previous studies, researchers assumed a container can only be located in a storage location when they study the integration of ITs scheduling and storage allocation. However, a container can be located in a number of potential locations and unfilled storage locations may occur in practical situations. Addressing such practical issues can also benefit terminal business.

Studies of transhipment operations in transhipment terminals always employ the same storage strategy to allocate storage space for the inbound, outbound and transhipment containers. Unlike the inbound and outbound containers, the storage locations of transhipment containers are not only related to the arriving vessel, but also involve the departing vessel. The study of storage space allocation for transhipment containers is necessary for transhipment terminals.

The delivery operations of transhipment containers are also different from the transportation of inbound and outbound containers. Dispatching a set of ITs to deal with a number of transhipment containers with unknown storage locations has not been considered by previous studies. This study therefore makes a significant contribution in this respect, which will benefit transhipment terminals.

1.2.2 Filling the Research Gap

This study fills the research gaps identified above by contributing the following innovations:

1) Modeling a novel ITAS system, integrating storage space allocation and the routing of ITs in gateway container terminals.

2) Developing a new hybrid genetic algorithm for handling ITAS.

3) Modeling ITs deployment strategy with consideration of ITAS.

4) Developing a new methodology for ITs deployment strategy.

5) Modeling storage space allocation for transhipment containers.

6) Modeling the delivery and storage of transhipment containers.

7) Developing a heuristic methodology for transporting and allocating transhipment containers.

1.3 Aim, Objectives and Scope of Research

The aim of this research was to study and develop an optimization approach for maximizing terminal throughput by adequately coordinating internal tractors assignment and scheduling (ITAS) with container storage location planning.

The first objective was to develop optimization methodologies for integrated scheduling. According to the classification of container terminals, integrated scheduling was considered for both gateway terminals and transhipment terminals. In the gateway terminals, the integration of truck scheduling and storage allocation was first investigated. In accordance with previous similar studies, truck scheduling and storage allocation was studied with consideration for the long-term truck deployment strategy. In the transhipment terminals, the problem of storage space allocation was firstly solved for transhipment containers. Then, transhipment container delivery and transportation scheduling were studied with the integration of storage space allocation for transhipment containers. Considering both the gateway terminals and transhipment terminals, internal tractors assignment and scheduling with container storage location planning was comprehensively examined.

The second objective was to evaluate the performance of the proposed algorithms for solving the abovementioned complicated integration problems. The third objective was to benchmark the improved efficiency gained from the integrated models.

The thesis framework, shown as Figure 1.1, illustrates the relationship between the tasks necessary to achieve the aim of this research.

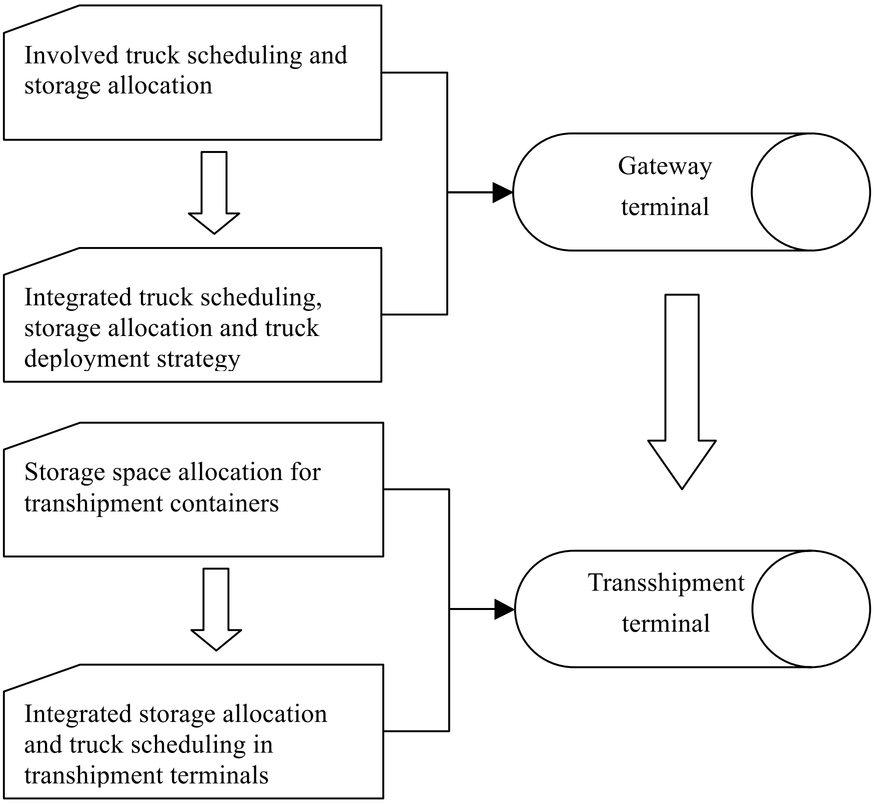

Figure 1.1 Thesis framework

Integrated scheduling was studied in relation to terminal operations, because in practice, there are numerous resource allocations and operations involved in a terminal. In this research, only internal tractors (ITs) assignment and scheduling related to yard side and quayside operations were studied.

1.4 Thesis Organization

The structure of this thesis is as follows:

In Chapter 2, a comprehensive review of operations in traditional container terminals is presented to demonstrate how terminals exchange containers between seaside and landside on daily bases, and what complications terminals are dealing with. Since different types of handling equipment result in different terminal operations and consequent decisions, this study only reviewed non-automatic traditional container terminal operations.

Chapter 3 provides a review of the literature on a range of seaside, storage assignment, and transport operations in container terminals. This reveals what has been studied on continuous dynamic berth allocation, quay crane assignment and scheduling, internal vehicle scheduling, and storage space assignment in terminals.

In Chapter 4, in order to determine the routing of trucks and proper storage locations for discharging containers from incoming vessels, yard truck scheduling and storage space allocation are integrated to minimize the summation of the delay of containers and the traveling time of yard trucks. A genetic algorithm (GA) is proposed to deal with the NP-hard problem. In the proposed GA, the guidance mutation approach and an exhaustive heuristic for local searching are used in order to force the GA to converge faster and more steadily. To test the performance of the proposed GA, both small scale and large-scale cases are studied. The comparison demonstrates that the performance of the proposed GA is reasonable and acceptable.

In Chapter 5, an extension problem for yard truck scheduling and storage allocation is studied. A novel insight is presented for the internal truck deployment strategy in container terminals, which is the determination of the strategy of employing renting and outsourcing yard trucks to meet operational daily transportation requirements and minimize the long-term cost of employing yard trucks. A mathematical model is proposed to deal with a practical problem, which is a better solution than the empirical method for employing different types of yard trucks.

In Chapter 6, the problem of storage location assignment for transhipment containers in transhipment container terminals is studied. Both the loading and unloading route distance is considered and transhipment containers are classified according the containers' characteristics. The problem is formulated as a mathematical model and solved by linear programming.

In Chapter 7, an enriched model for transhipment container transport and storage is proposed. A mathematical model is proposed for yard operations decision making and integration with berth side operations, and a heuristic method is proposed for solving the model. The results attest to the efficacy of both.

In Chapter 8, a summary and conclusion of the study is presented, and recommendations are made for future related research.

Chapter 2 Background

2.1 Introduction

Containers are standard-sized metal boxes that are used for transporting cargo between different locations. They have been used in the international sea freight transportation market for more than six decades and are well accepted due to inherent advantages. Containers are the foundation for a unit-load-concept, which benefits the loading and unloading process by avoiding the unpacking operation at each point of delivery. Moreover, uniformed metal containers provide protection against weather, pilferage and damage, as well as simplifying scheduling, monitoring and controlling. The most commonly used standard container is the TEU, which is 20 feet long, 8 feet wide and 8.5 feet high; the forty-feet-equivalent-unit (FEU) is twice its length. See Figure 2.1.

Figure 2.1 TEU (right) and FEU (left)

Since the first regular sea container service about six decades ago, cargo has become increasingly containerized. Nowadays, the throughput of containers worldwide is more than 500 million TEUs a year. The increasing large number of container transhipments not only improves economic efficiency and market share, but also requires more efficient management of container terminal operations. Efficiency of a terminal determines its competitiveness in the terminal industry. Accordingly, terminals have been devoting much effort to shortening the vessel staying time, and in minimizing the turnaround time by developing various decision support systems (Steenken *et al*., 2004).

A container terminal is an open system of cargo flow, which delivers inbound and outbound containers into and out of the terminal. The operations in container terminals, as shown in Figure 2.2, are always the same though terminals differ in size, function, and geometric layout (Günther and Kim, 2006).

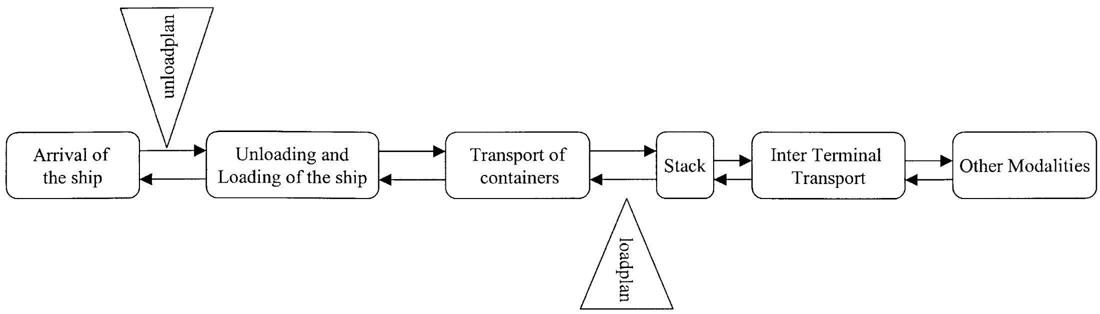

Figure 2.2 Operations at a container terminal (source: Vis and Koster, 2003)

When a vessel arrives at a port, it moors into the berth allocated to it several weeks before. The berth allocation system gives the vessel a time period for staying. Once the vessel is berthed, it will not be moved until its departure time (Lim, 1998). Several QCs are assigned to the vessel for loading and unloading the containers. A QC schedule, which specifies the service sequence of bays in a ship and the time schedule for the services (Kim and Park, 2004), is assigned to each QC. In order to store inbound containers, yard space needs to be pre-assigned (Kim and Kim, 1999). After the allocation of yard space, a set of ITs is dispatched to deliver the containers between the quayside and yard side. Usually, unloading precedes loading and containers should be served following precedence relations (Bierwirth and Meisel, 2010). After the completion of the unloading tasks, outbound containers start to be loaded to the vessel from the yard (Ng and Mak, 2006). The vessel will not depart until loading operations have been completed.

Container terminal operations can be classified into berth operations, quayside operations, transport operations, storage yard-side operations and gate side operations, as shown in Figure 2.3. The full container terminal system and the classification of container terminal systems are discussed in section 2.2. The berth and quay areas are considered as seaside. The detailed seaside operations are discussed in section 2.3. The transport operations are discussed in section 2.4. The operations occurring in the storage yard are discussed in section 2.5. In section 2.6, the performance measures of container terminal systems, seaside operations, transport operations and storage yard operations, which have been commonly applied by researchers, are described. Finally, a summary is given in section 2.7. Since the gate area is not within the scope of this thesis, gate area operations are not discussed.

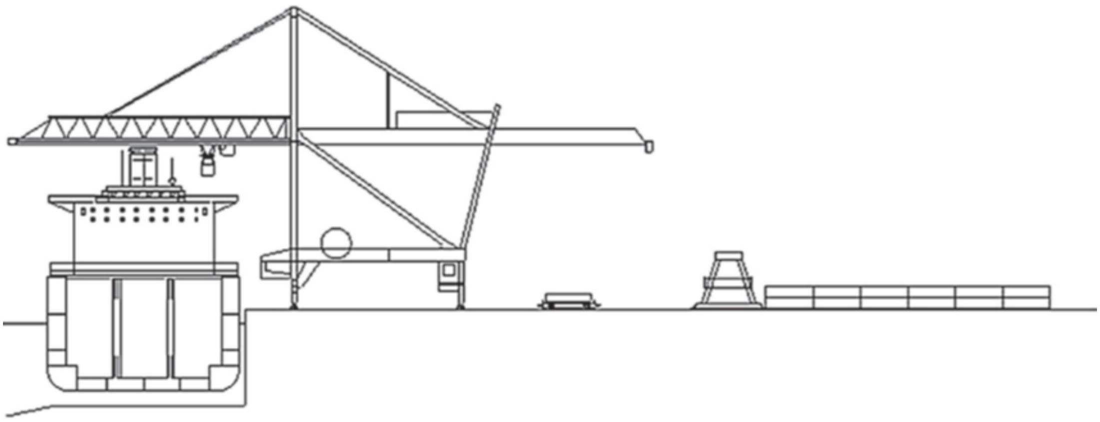

Figure 2.3 Container terminal main areas (source: Carlo *et al*., 2014a)

2.2 Container Terminal Systems

Container terminals make great efforts to enhance their competitiveness. In order to enlarge handling capacities, terminals are forced to replace older equipment with more efficient ones. Another way is to use new technique handling equipment, such as the automatic stacking crane that is also known as an automatic lifting vehicle (ALV). One more approach is to use existing equipment more efficiently by means of powerful information technology and logistics control software systems, including optimization methods (Günther and Kim, 2006).

2.2.1 Direct Transfer System and Indirect Transfer System

Different combinations of handling equipment are found in different kinds of container terminals. All terminals use QCs to unload containers at the quayside. Containers can be transported between the quayside and yard side by trucks with trailers, automatic guided vehicles (AGV, Figure 2.4), straddle carriers (SCs, Figure 2.5), yard gantry cranes (YGC, Figure 2.6), and reachstackers (Figure 2.7). Generally, terminals can be categorized according to the types of handling equipment they use. There are two principal categories of terminals: Direct Transfer System (DTS) and Indirect Transfer System (ITS). The former only uses SCs or ALVs, which can lift containers on their own for transportation and stacking. The latter uses yard gantry cranes for stacking containers.

Figure 2.4 Example of AGV

Figure 2.5 Example of SC

Figure 2.6 Example of YGC

Figure 2.7 Example of reachstacker

The decision on which category of terminal to construct depends on space restrictions, cost, and historical data (Stahlbock and Voβ, 2008b). In Asian regions, terminals typically rely on ITS as it requires less land space, which is limited and expensive. Vis and Harika (2004) concluded that using either AGVs or ALVs does not impact the unloading times of ships. With reference to Duinkerken *et al.*(2006), more AGVs are needed to handle the same number of containers than ALVs. Bae *et al.*(2011) also compared the operational productivities of AGVs and ALVs. Simulation results show that the productivity of AGVs can equal ALVs, except that with AGVs the throughput of QCs is exceptionally high when using tandem double-trolley QCs.

2.2.2 Automatic System and Non-automated System

Automatic and non-automatic are the two main configurations of yard layouts (Lee and Kim, 2013; Liu *et al*., 2004; Petering, 2008; Carlo *et al*., 2014b). The main difference between these two container terminal systems is the location of the input/output (I/O) point, i.e. where the internal vehicles and the YCs exchange containers (Carlo *et al*., 2014b). The automatic container terminal system usually consists of AGVs, automatic gantry cranes, and automatic straddle carriers as shown in Figure 2.8. Automation is controlled by a series of powerful systems, such as the Global Positioning System. In non-automatic systems, the internal vehicles and the YCs exchange containers at parallel truck lanes in the yard (see Figure 2.9). The internal vehicles and YCs usually are non-automatic in this system. It is known that the non-automatic system is common in large Asian terminals, while the automatic layout configurations are usually implemented in large European terminals.

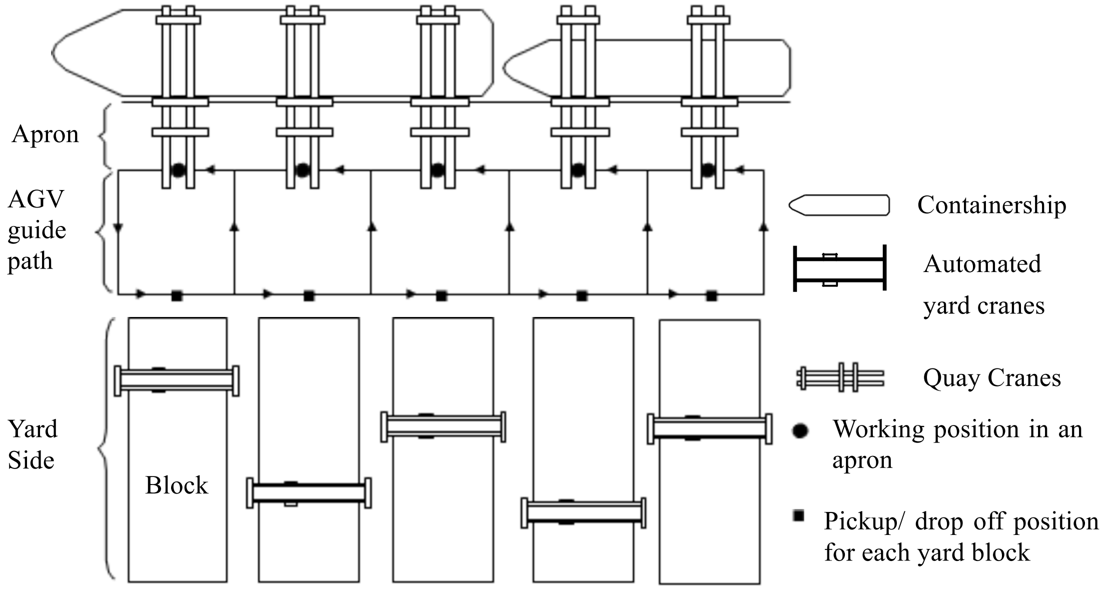

Figure 2.8 Layout of automated container terminal

Figure 2.9

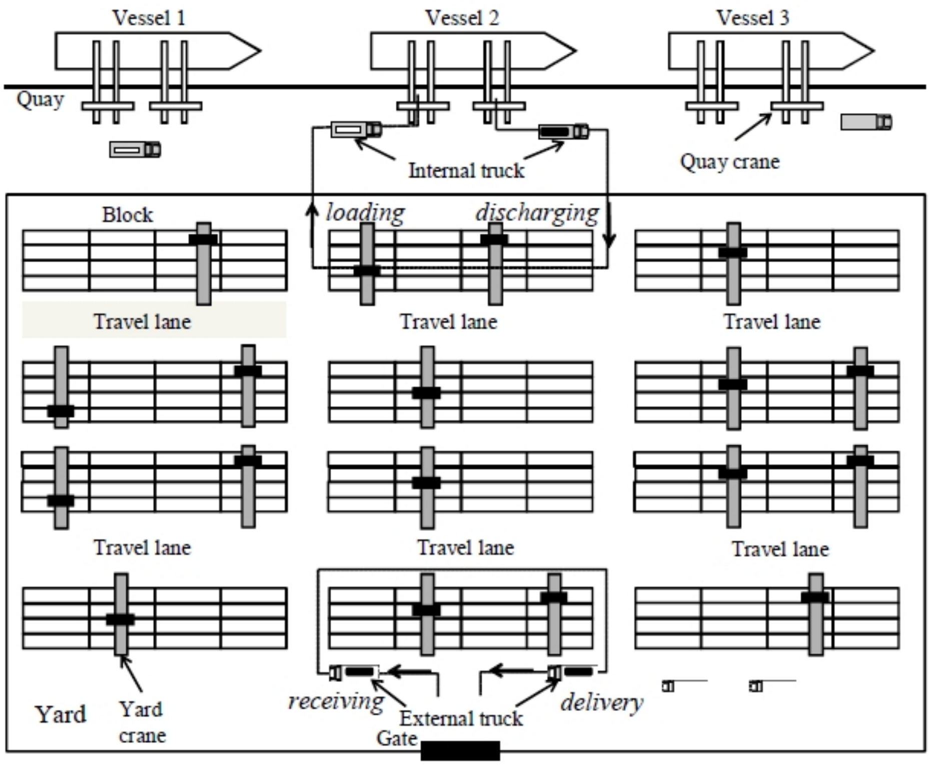

Figure 2.10 Layout of non-automated container terminal (source: Jeong *et al*., 2012)

Container terminals prefer to use automatic equipment, particularly in regions where the labor cost is high. With reference to Liu *et al.* (2002), automation can dramatically increase throughput and reduce costs. However, according to Nam and Ha (2001), automatic handling equipment cannot ensure that an unmanned system is better than a conventional system with respect to both cost and productivity. The performance of automation and manned systems depends on the characteristics (Nam and Ha, 2001). According to Yang and Shen (2013), automation in a container terminal needs a large amount of investment, and an advanced automation control system needs constant development. As automation in container terminals is not yet prevalent, the non-automatic container system, which is employed in most Asian terminals, is the major focus of this research.

2.3 Seaside Operations

2.3.1 Berth Allocation

A marine vessel's journey follows a predetermined schedule, which records the travelling sequence of marine container ports. However, the arrival time of a vessel in marine container transport is always behind schedule because of the long travel distance, weather conditions, and some unpredictable situations (Notteboom, 2006). Thus, container terminals usually apply arrival-planning strategies to manage the vessel arrival process (Lang and Veenstra, 2009).

After the arrival time of a vessel is known for certain, the container terminal will arrange for the vessel to move into the harbor with an assigned berth so that it can moor in the port, as shown in Figure 2.10. Based on information of the available berths at the quay, terminals make a decision on the allocation of berths for vessels. This is commonly known as the Berth Allocation Problem (BAP). The BAP usually concerns the berthing positions, turnaround time and mooring times of vessels under dynamic arrival situations. In the dynamic arrival case, the expected arrival time of the vessels is considered within a given planning horizon; in static arrival cases, it is assumed that vessels can be moored to berths at any time. The static case can be viewed as a special case of the dynamic case where the arrival times of vessels are zero. Thus, in the literature, dynamic arrival cases are mainly studied.

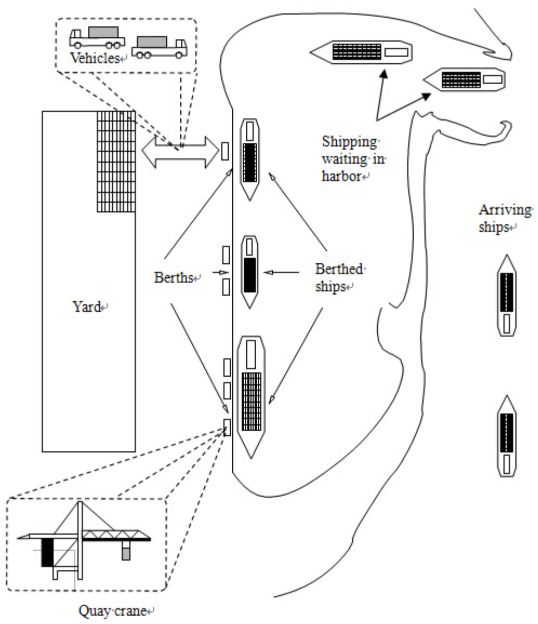

Figure 2.11 Vessel berthing illustration (source: Cordeau *et al*., 2005)

The BAP can be further divided into discrete BAP, continuous BAP and hybrid BAP according to the layouts of berths, as shown in Figure 2.11(a–c). In the discrete case, the quayside is partitioned into several berths and only one vessel can be assigned to a berth. In contrast, the continuous berth case allows a vessel to be moored anywhere along the quay. Finally, in the hybrid berth case, vessels are allowed to occupy more berths or share a berth, which means the berthing area can be discrete and continuous within a berth.

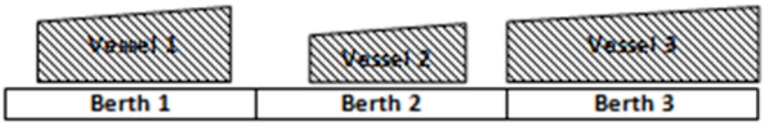

Figure 2.11a   Illustration of discrete berth layout

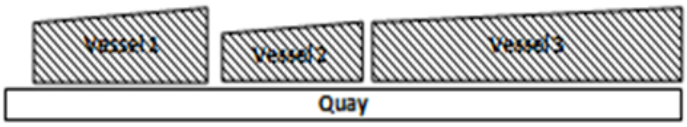

Figure 2.11b   Illustration of continuous berth layout

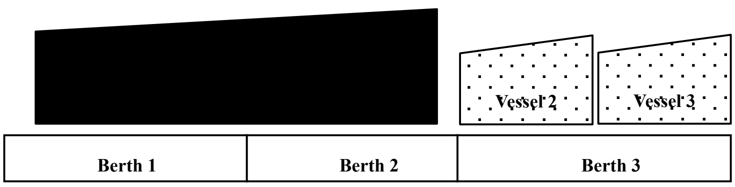

Figure 2.11c   Illustration of hybrid berth layout

2.3.2 Quay Crane Assignment and Quay Crane Scheduling

Once a vessel is moored in a berth, one or more QCs are assigned to the vessel to unload containers from the vessel following an unloading plan. The QC is important equipment that is located on the shore, usually rail-mounted and non-automated, shown in Figure 2.12. The QCs pick up inbound containers from the decks of vessels and drop them off on internal transport vehicles during the unloading procedure. On the other hand, the QCs load outbound containers from internal vehicles and put them on the decks of vessels during the loading procedure. The internal vehicles travel between QCs and the storage yard for container delivery. The problem of assigning a certain number of QCs to vessels for loading and unloading is known as the Quay Crane Assignment Problem (QCAP). The schedule of loading outbound and inbound containers by quay cranes is known as the Quay Crane Scheduling Problem (QCSP). The QCSP refers to the plan that indicates the allocation of the outbound and inbound containers loaded by each quay crane, and the loading sequence plan of each quay crane.

Figure 2.12 View of QCs

2.4 Storage Yard Operations

2.4.1 Storage Allocation

In general, the shape and the size of a storage area depend on the physical configuration of the yard. It can be further divided into different zones according to the container specifications and needs of the terminal. Each zone is then further divided into rectangular shaped storage regions called blocks, and are organized into bays, rows, and tiers. The storage location of a container, which is known as the Storage Allocation Problem (SAP), is decide by the block, bay, row, and tier (Steenken *et al*., 2004).

There are also several lanes of spaces for storing containers in stacks, and a lane for ground vehicles to pick up and deliver containers. In every stack, containers are stacked on top of each other (Linn *et al*., 2003). When assigning storage locations for containers, reshuffling of containers within the block in the storage location should be avoided. Besides, some specific constraints may also be taken into consideration when planning the storage location, for instance, whether the container is for import or export, the date of departure, and the type of the container. (Günther and Kim, 2006).

2.4.2 Yard Crane Scheduling

The YCs transfer containers from internal vehicles at a specific position in the storage yard and vice versa. Both inbound and outbound containers are stacked in the storage yard for temporary storage, and YCs are employed to stack the containers. The YCs are essential equipment that is located in the yard, usually rubber-tired or rail-mounted, as shown in Figure 2.13 and Figure 2.14. The rubber-tired gantry crane (RTGC) can travel freely both horizontal and orthogonal as the tires can be rotated 90 degrees. The rail-mounted gantry crane (RMGC), on the other hand, can only move on its rails.

Figure 2.13 View of RTGC

Figure 2.14 View of RMGC

Yard crane scheduling (YCS) refers to the dispatching and routing of YCs. The dispatching of YCs determines the containers assigned to YCs, while the routing of YCs determines the sequence of containers handled by YCs. In general, YCS indicates the allocation of containers to YCs and the container handling sequence of YCs.

2.5 Transport Operations

Containers are transported by internal tractors (ITs) between the quay and yard. ITs are specially designed engineering vehicles that are used to deliver containers, as shown in Figure 2.15. Once the QCs unload containers from vessels to ITs, the ITs transport the containers from the quay to the yard along the passing lane. Then the containers are temporarily stored in the yard by the stacking of YCs, which releases the ITs to go for the next jobs. The loading procedure is the opposite process of the unloading procedure. The problem of allocating a number of ITs to handle a number of loading and unloading containers is handled by ITAS, which determines the vehicles' travelling path, the schedules to handle all the jobs and which vehicles perform each movement.

Figure 2.15 View of ITs

ITAS involves the scheduling of ITs to transport different inbound and outbound containers between vessels at the quayside and the yard side, as shown in Figure 2.16. ITAS can be studied at three planning levels: strategic level, tactical level, and operational level. The strategic level is related to the terminal design and involves long-term decisions regarding terminal layout, terminal equipment, berth and yard capacity, strategic alliances with shipping companies and multi-modal interfaces (Vacca *et al.*, 2007). From the strategic perspective, ITAS refers to the determination of the number of ITs that should be purchased. This is because insufficient ITs cannot meet the transportation requirement and owning excessive ITs may be a waste of money.

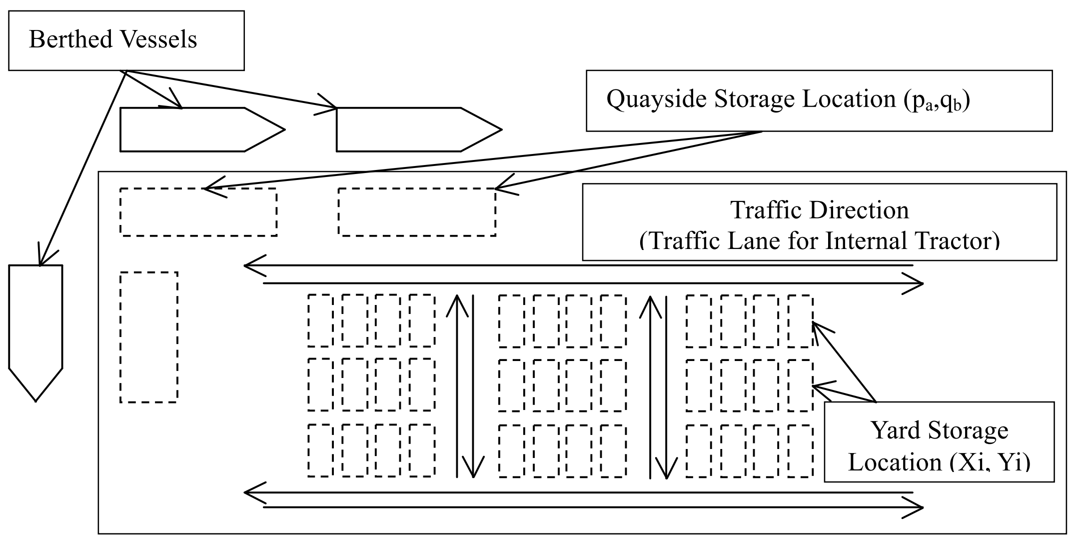

Figure 2.16 Outline of operations involved in ITAS

On a tactical level, ITAS is the determination of the minimum number of vehicles required each day (Vis *et al.*, 2001), since too many ITs may cause congestion both on the yard side and the quayside, and insufficient ITs may delay the departure of a vessel.

ITAS can also be considered at the operational level, which is related to operative planning and real-time control (Vacca *et al*., 2007). The problem is how to dispatch ITs to transport a number of inbound and outbound containers from the quayside to the yard side, and vice versa. Since transport optimization in a terminal not only means reducing transport times but also synchronizing the transport with the loading and unloading activities of the QCs (Steenken *et al*., 2004), it is usually related to the productivity of QCs.

2.6 Container Terminal Performance

There are three major factors involved in measuring marine terminal performance: 1) productivity, 2) utilization, and 3) service rate (Theofanis *et al*., 2009; Le-Griffin and Murphy, 2006; Bierwirth and Meisel, 2014). The common productivity measures of crane, berth, and yard are described in Table 2.1.

Table 2.1 Common productivity measures of crane, berth, and yard (source: Le-Griffin and Murphy, 2006)

	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	

The specific performance measures for seaside, yard side and transport operations are shown in Table 2.2, Table 2.3 and Table 2.4.

Table 2.2 Specific performance measures for yard-side operations (source: Carlo *et al*., 2014a)

No.	Description
1	Number of moves required
2	Task completion time (typically makespan)
3	Yard crane distance travelled-related metrics
4	Due times-related metrics
5	Utilization of yard space
6	Utilization of gantry cranes
7	Any other

Table 2.3 Specific performance measures for seaside operations (source: Bierwirth and Meisel, 2010; Carlo *et al*., 2013)

No.	Description
1	Waiting time of the vessel
2	Handling time of a vessel
3	Completion time of vessel
4	Necessary speedup of vessel to meet expected arrival
5	Tardiness of vessel with respect to due date
6	Deviation between vessel arrival order and service order
7	Rejection of a vessel
8	Terminals' resource utilization
9	Deviation between actual and desired berthing position
10	Travel distance between assigned berth and assigned yardblocks
11	Any other

Table 2.4 Specific performance measures for transport operations (source: Carlo *et al*., 2014b)

No.	Description
1	Number of vehicles (including investment and operational costs)
2	Task completion time (typically makespan)
3	Transfer vehicle distance traveled-related metrics
4	Due times-related metrics
5	Average vessel processing time
6	Other financial cost not related to number of vehicles
7	Any other

2.7 Summary

In this chapter, a brief review of container terminal operations is introduced with the objective of showing: (1) the operations involved in handling cargo in terminals; (2) how these handling operations are executed by different kinds of equipment; and (3) what attributes measure container terminal performance. This knowledge is helpful for understanding the approach to achieving the aim of this study.

By reviewing the container terminal system, it was observed that operation problems exist in each different subsystem because of the different characteristics of the subsystems. However, the operation of each subsystem is affected by other subsystems to a great extent, which is why container terminal systems should be investigated as a whole.

In the next chapter, a literature review of research articles dealing with container terminal operation problems and proposing highly efficient solutions is provided.

Chapter 3 Literature Review

3.1 Introduction

There are a considerable number of research articles related to container terminal operations. This literature review presents research that has been done in the area of container terminal operations and logistics as well as topics related to it. The presentation of research articles aims to achieve two goals: the first goal is to share the previous study of container terminal operations; the second goal is to demonstrate that few studies have addressed issues that are similar to those in this thesis. A comprehensive literature review of container terminal operations within the scope of this research is presented in the following subsequent chapters. Independent reviews of decision problems in seaside operations, container transport operations, and storage yard operations are given in section 3.2, section 3.3 and section 3.4, respectively. Integration decision problems is reviewed in section 3.5. Finally, a brief summary is given in section 3.6.

3.2 Decision Problems in Seaside Operations

3.2.1 Berth Allocation Problem

The BAP seeks suitable berthing positions for arriving vessels with consideration of physical characteristics, e.g., berth length and vessel draft. Lim (1998) first transformed the problem to a restricted form of the two-dimensional packing problem and proposed a graph-based theoretical model. The reformulated specific berth planning model was proven to be NP-complete in terms of computational complexity theory.

Park and Kim (2002) studied the BAP with a fixed handling time for a vessel. The objective was to minimize the tardiness of a vessel against the expected due date and deviation between the actual and desired berthing positions. Based on Park and Kim (2002) and Moon (2000), Kim and Moon (2003) proposed a mixed integer programming (MIP) for the determination of berthing times and positions of containerships, with the same objective as Park and Kim (2002). A simulated annealing algorithm was developed for the solution, and near-optimal results were obtained. Guan and Cheung (2004) also studied the BAP considering the fixed handling time of the vessel with the objective of minimizing the handling time and waiting time of the vessel. Later, Wang and Lim (2007) further studied the BAP with consideration of waiting time, deviation between actual and desired berthing position, and rejection of a vessel. A new stochastic beam search was proposed for the solution. Lee *et al.* (2010) studied the continuous and dynamic BAP with a fixing handling time of a vessel. The proposed methodology was able to find all the possible locations in the Time-space diagram for the next vessel. Two versions of the greedy randomized adaptive search procedure were developed for the solution.

A few publications described the BAP by assuming that the handling time of a vessel depends on its berthing position. Imai *et al*. (2005) presented a heuristic approach for the continuous and dynamic BAP. The proposed approach aimed to provide a more flexible berth allocation plan for major container ports that serve vessels in diverse ship sizes. Ganji *et al*. (2010) proposed a GA-based approach for solving the BAP that was modeled by Imai *et al.* (2005). Both large and small-scale instances were studied. The results showed an interactive relationship between quay length and handling time. Lee and Chen (2009) further studied the BAP by considering the required clearance distance between vessels and shifting the position of a vessel to make space for another one.

Some researchers further developed the BAP by defining the stochastic handling time of a vessel. Zhen *et al*. (2011b) studied the BAP with consideration of uncertain arrival and handling times of a vessel. A meta-heuristic approach was proposed to solve the problem in large-scale practical situations. Xu *et al.* (2012) further investigated the BAP problem by proposing a robust formulation of the problem. The proposed formulation aimed to balance the customer service level and the subsequent operations, so as to make a reduction on the frequency and scale of adjustments during application of the berth plans.

3.2.2 Quay Crane Assignment Problem

The QCAP seeks to determine the number of prearranged cranes for vessels. Publications that studied the QCAP always assumed a specific type of BAP. For this reason, the QCAP is not reviewed separately from the berth planning process. The integration problem of the QCAP and the BAP is discussed in the following section.

3.2.3 Integration of Seaside Operations

In a couple of publications, BAP is integrated with QCAP to improve crane utilization. Meisel and Bierwirth (2006) studied the integration problem by first generating a set of QC-to-vessel assignment patterns, and secondly by fixing the berthing position, berthing times and crane assignment by using a priority rule. The objective was to minimize the cost for manning QCs. Later on, Hendriks *et al.* (2010) minimized the maximum number of QCs required to handle vessels in a cyclic berth. The arrival times of vessels were considered as variables and a robust optimization model was proposed.

A further approach that included due dates of vessels was provided by Legato *et al.* (2008). Here, the berthing times, berthing positions and due dates of vessels were generated by using the model proposed by Park and Kim (2003). Meisel and

Bierwirth (2009b) minimized vessel waiting times and unprocessed transhipments in a cut-and-run policy environment. In this policy, vessels cannot be served completely up to the time window and unprocessed transhipments are ignored. The solution methods are the same as used by Meisel and Bierwirth (2009a). Chang *et al.* (2010) formulated the problem as a non-linear mathematical model with the aim of minimizing the total berthing position deviation and the total penalty and energy consumption of the QCs. Blazewicz *et al*. (2011) studied the problem to minimize the maximum completion time of all vessels by transforming the problem into a non-preemptive moldable task-scheduling problem. They solved the problem by using a suboptimal algorithm, which first obtains a solution from the continuous version of the moldable task-scheduling problem, and then transforms the solution into discrete version of the problem. Hendriks *et al*. (2012) studied the problem in multi-terminal ports where berths are located in different terminals operated by the same operator. An MIP was proposed and a two-step optimization approach was developed for solution. Yang *et al*. (2012) also studied the integration problem of BAP and QCAP and by combining the formulations proposed by Guan and Cheung (2004) and Legato *et al*. (2008), they developed a nested loop-based evolutionary algorithm; a GA and a heurist-based GA were used in the first and second inner loop respectively, and an evolutionary algorithm was used in the outer loop.

A decision support system (DSS) is also a feasible method for solving integration problems. Urasvas (2014) proposed a DSS for optimizing operations in the seaside. A mathematical model that combined BAP, QCAP and QCSP was developed for solving the problem of positioning the vessels in the decision space without overlapping each other, while minimizing the total service time of the ships and minimizing the labor cost. After a certain number of iterations, the DSS generated satisfactory solutions.

3.3 Container Transport Operation

3.3.1 Number of Vehicles Required

Murty *et al*. (2005a) and Murty *et al*. (2005b) developed a DSS for daily operations at a container terminal, involving the operations of container transportation, yard crane assignment, storage space allocation and appointment times for external trucks. To minimize the QC processing time and makespan of a vessel, the minimum number of yard trucks was determined by integer programming. Hong Kong International Terminals saved approximately US$6 million per year by employing less yard trucks according to Murty *et al*. (2005b). Kang *et al*. (2008) optimized the size of the transportation fleet for unloading operations under the cyclic queue model. The problem was solved by using a Markovian decision process and a simulation model.

With respect to these studies and to relate the container transport operation, this research investigated another problem to benefit the terminal's long-term economic benefits. As container throughput fluctuation always occurs, the number of vehicles required each day might not be fixed. Thus, terminals can rent a few extra vehicles when the throughput becomes larger, and can meet the throughput by its own trucks when the throughput becomes smaller. This study investigated the vehicle deployment strategy problem in combination with internal truck scheduling and storage allocation problems in container terminals.

3.3.2 Internal Vehicle Routing and Dispatching

3.3.2.1 Internal Vehicle Routing

Koo *et al*. (2004) studied the problem of determining the minimum fleet size required and travel distance to serve all containers within a predefined planning horizon under static transportation system, in which all the transportation requirements are predefined at the beginning of the planning horizon. The problem was solved using a two-phase heuristic algorithm and the computational results were compared with two existing methods.

Nishimura *et al*. (2005) studied a dynamic dispatching strategy of yard trailers, in which a single yard trailer can serve several QCs. The computational results showed that the dynamic yard trailer dispatching strategy can cut vehicle fleet size by reducing the travel distance of empty yard trailers. Nishimura *et al*. (2005) also pointed out the difference between the vehicle routing problem and trailer routing problem. First, the tours considered in the trailer routing problem are independent and not connected. Second, the trailer routing problem deals with multi-trailers that permit a mixture of pickup and delivery in a tour.

Ng *et al*. (2007) studied the problem of scheduling a set of yard trucks to transfer a number of containers with sequence-dependent processing times and ready times. The NP-hard problem was formulated as an MIP and solved by using GA so as to minimize the makespan of a vessel.

Zeng *et al*. (2009) studied the multi-crane oriented scheduling problem. In contrast to single-crane oriented scheduling, yard trailers can be shared by multi-yard cranes. Two different models were developed. In the first model, yard trailers were shared by QCs of different ships. In the second model, yard trailers were shared by QCs of the same ship. It was concluded that the multi-crane oriented scheduling method can improve terminal efficiency by decreasing yard trailers' travel distance.

3.3.2.2 Internal Vehicle Dispatching

The study of internal vehicle dispatching rules start with the single-cycling rule, by which each vehicle serves only one crane. Bish *et al*. (2001) analyzed unloading import containers from arriving vessels to potential storage locations in the yard, and dispatching vehicles to the containers in order to minimize the unloading time of a vessel. It was proved that the problem is an NP-hard problem and solved by a heuristic algorithm. Kim *et al*. (2004) studied the loading sequence for export containers in container terminals with yard cranes and yard trucks. A beam search algorithm was proposed for minimizing the handling time of cranes and trucks. Li and Vairaktarakis (2004) studied vehicle dispatching with a single crane and a single containership. The objective was to minimize the makespan of a vessel, and three heuristic algorithms were proposed. Zhang *et al*. (2005) presented three integer programming models for dispatching vehicles to transfer a number of containers in the unloading phase at container terminals.

The double-cycling dispatching rule, by which each vehicle serves several cranes, was subsequently studied by many researchers. Soriguera *et al*. (2006) simulated the operations in the Port of Barcelona, Spain and the results demonstrated that a container terminal can achieve economic benefits by assigning vehicles to entire berths rather than a specific quay crane. Chen *et al*. (2007) considered the scheduling of yard trucks, yard cranes and QCs as an extension of the hybrid flow-shop scheduling problem. The objective was to minimize the makespan of a vessel and an

MIP was provided. Alessandri *et al*. (2007) studied container transfer in intermodal terminals. The containers transferred by different types of equipment, i.e., containership, rail and yard truck, were represented by a system of queues in order to simulate the waiting and movements of containers. A solution was provided by the dynamic evolution of these queues to minimize the transfer delays of containers. Lee *et al*. (2010) studied vehicle dispatching in transhipment hubs by considering the quay crane, yard crane and vehicle capacity to minimize the makespan of a vessel. Both the neighborhood search and GA were used. Petering (2010) investigated how real-time dual-load yard truck control systems are affected by long-run average quay crane throughput rate, applying a discrete event simulation model of a transhipment terminal.

3.4 Decision Problems in Storage Space Assignment

3.4.1 Storage Space Assignment of Individual Containers

In earlier studies, the containers' arrival and departure information, in and out of the storage yard, were assumed to be ignored or obeyed probability distributions. Kim and Kim (1999) addressed allocating storage space for import containers and a segregation policy was considered, in which the authors analysed cyclic and dynamic arrival rates. The objective was to minimize the number of re-handling operations. A deterministic and a stochastic models were proposed. Preston and Kozan (2001) studied the optimal container storage policy under different container handling scheduling, i.e. first-come-first-served, last-come-first-served and random. Computational results showed that the type of schedule had no effect on the transfer time if a good storage layout was used.

More practical circumstances were later considered and hierarchical approaches adopted for individual container assignment. Zhang *et al*. (2003) studied the SAP. A rolling-horizon approach was proposed in which the problem was decomposed into two levels. The first level aimed to balance two types of workloads among the blocks, while the second level focused on minimizing the total distance to transport the containers between their storage blocks and the vessel berthing locations. Guldogan (2010) investigated the assigning of containers in specific locations. The problem was solved by first assigning containers to blocks and second to particular locations within the chosen block. In the first step, the workload balance, vehicle travel distance and vehicle fleet size were taken into account, while for the second step, containers were clustered in accordance with their departure time. Ng *et al.* (2010) studied locating outbound containers on ports with cyclical patterns. An integer programming model was proposed and an iterative constructive heuristic approach was presented for solution. Chen and Lu (2012) assigned storage locations for individual outbound containers in their hierarchical approach. Sharif and Huynh (2013) studied assigning individual containers in terminal storage space by modeling the container terminal as a network of gates, yard blocks and berths. The model utilized an ant-based control method to determine the route for each individual container based on two objectives: (1) balance the workload among yard blocks, and (2) minimize the distance traveled by internal trucks between yard blocks and berths.

3.4.2 Storage Space Assignment of Groups of Containers

Kim and Park (2003) addressed the assigning of storage space for outbound containers to increase the storage space utilization and loading operation efficiency. Nishimura *et al*. (2009) studied container assignment in storage yards of transhipment terminals. It was formulated as an MIP and the corresponding Lagrangian relaxation was presented. A heuristic algorithm was used to minimize the total container handling time. Woo and Kim (2011) addressed the determination of the size of storage space for export containers. Experimental studies showed that the square root of arrival rate rule, where empty stacks are reserved for a container group in proportion to the square root of the arrival rate of containers in that group, performed best by using a simulation study.

3.5 Decision Problems in Integrated Operations

3.5.1 Integration of Container Transport Operation with Storage Space Assignment

In the literature, a few studies deal with both internal vehicles scheduling and storage space allocation problems. Bish *et al*. (2001) studied the two problems, but solved each problem separately. They assumed that a container can be stored in a number of reserved locations in the yard for storage space allocation problem, and containers are delivered between yard and vessel by yard trucks which carry one container at a time for vehicle scheduling problem. The solution involved two steps. The first step was to solve the storage space allocation problem by disregarding the vehicle scheduling, and the second step solved the vehicle scheduling problem for the storage space allocation obtained from the first step, using a heuristic algorithm. Bish (2003) further studied the determining of a storage location for each discharging container, dispatching vehicles to the containers, and scheduling the unloading and loading operations on each quay crane. The objective was to minimize the maximum turnaround time of a set of vessels. Bish *et al*. (2005) developed another heuristic algorithms for solving the problem.

Han *et al*. (2008) studied yard truck scheduling and the SAP as an integration in transhipment terminals. A mathematical model was proposed and the model was solved by heuristic approaches. Lee *et al*. (2008) proposed an integer programming model to deal with the problem of yard truck scheduling and storage allocation. This paper considered the two problems as a whole instead of solving each aspect separately. The objective was to reduce congestion and idling time of the yard trucks in order to decrease the makespan of the discharging containers.

Later on, Lee *et al*. (2009) presented an MIP for deterministic storage assignment and vehicle scheduling for import containers. Lee *et al.* (2009) further extended the previous study and proposed another integrated model for the yard truck scheduling and storage allocation problem with consideration of container loading and unloading. A hybrid insertion algorithm was proposed for the solution and 20 containers were considered in the computational experiments. Cao *et al.* (2010) proposed an integrated model for internal vehicle and yard crane scheduling. Two different Benders' decomposition based algorithms were developed.

From the literature, it is known that internal vehicle scheduling and SAP are highly interrelated. However, previous studies may limit practical applications. Therefore, in this thesis, the problem is further enhanced by taking into consideration all available storage locations in the terminals. In other words, the number of storage locations can be larger than the number of import containers. This modified approach is more complicated than the previous ones as the number of possible solution combinations increase dramatically. A new hybrid GA is proposed to deal with the new integrated problem.

3.5.2 Integration of Seaside Operation with Container Transport Operation or Storage Space Assignment

Some researchers have studied the integration of storage space assignment and seaside operations. Salido *et al.* (2012) studied the combinatorial aspects of the BAP, the QCAP, and container-stacking problem. The solution used a DSS, in which a meta-heuristic called greedy randomized adaptive search was developed for the BAP and QCAP. Furthermore, a domain-oriented heuristic planner was developed for allocating the containers in the appropriate storage spaces.

A number of researchers investigated integrating yard crane scheduling and yard truck scheduling. Chen *et al*. (2013) simultaneously studied QC scheduling, YC scheduling and yard truck transportation in container terminals. The integration was to determine the start and finish times of the containers on each crane and the routes of the yard trucks and the yard truck assignment to the containers. The approach was formulated as a constraint programming model and a three-stage algorithm was formulated with the objective of minimizing the makespan of loading and unloading jobs. Tang *et al*. (2014) addressed joint QC and yard truck scheduling, and studied both unidirectional and bidirectional flow to minimize the idle time of QCs and yard trucks between performing two successive jobs. An improved particle swarm optimization algorithm was developed. Lu and Le (2014) addressed the scheduling of YC, QC, and yard trucks to minimize the time of YC operation with the coordination of yard truck and YC task assignment. The uncertainty factors, i.e., speed of loading and empty yard truck, time of YC hoisting/lowing operation and speed of YC, were considered in the proposed mathematical model, solved by a particle swarm optimization algorithm.

A set of studies integrated the seaside operation, transport operation and storage space assignment as a whole. Petering (2011) studied a seaport container terminal's long-run QC rate that depended on strategic and tactical container terminal management. A simulation study was proposed and the results showed that the long-run average quay crane rate depended on: storage yard capacity, yard cranes and trucks fleet size, the ability to accommodate truck substitutability and the overall size of the terminal.

Zhen *et al*. (2011a) studied berth planning and yard planning, which integrated QC assignment, berth allocation and yard vehicle scheduling. The yard crane assignment was described by the quay crane profile concept from Giallombardo *et al*. (2010). An

MIP was proposed to minimize the service cost and the average route length for loading and unloading and a heuristic algorithm was developed. He *et al*. (2015) proposed a mathematical model for the formulation of integrated QC scheduling, YC scheduling, and IT scheduling. A simulation-based optimization method was developed for an efficient solution, where the optimization algorithm integrates the GA and the particle swarm optimization algorithm.

This thesis expands Zhen *et al*.'s (2011a) work and further investigates transhipment containers delivery and storage allocation. To the best of the authors knowledge, no literature exists to examine the yard truck scheduling and storage allocation in transhipment container terminals. The study of transhipment containers delivery and storage is expected to not only reduce the turnaround time of vessels, but also connect to the seaside operations and integrate the seaside and yard-side operations in the whole container terminal system.

3.6 Summary

The chapter provides a brief review on the current literature focusing on container terminal seaside, transport and storage space assignment operations. The objective of this review is to comprehend and extend the current work through defining gaps and addressing them to some extent. The review revealed that not many studies have been carried out on factors affecting container terminal throughput by internal tractors assignment and scheduling. One of the contributions of this study is therefore to redress this by developing an analytical model relating to internal tractors scheduling and assignment. In reviewing the literature on seaside, transport and storage space operations, the relationship of these operations through mathematical and analytical approaches has been obtained.

Chapter 4 Storage Space Assignment and Yard Truck Scheduling in Gateway Container Terminals

4.1 Introduction

From the common operations at container terminals and a review of relevant literature presented in Chapters 2 and 3, it is found that yard truck scheduling (YTS) and the SAP are highly interrelated. This chapter aims to determine the routing of trucks and proper storage locations for discharging containers from incoming vessels, by integration of YTS and the SAP to minimize the summation of delay and yard truck travel time.

YTS refers to the scheduling of yard trucks to serve the transportation of loading/unloading containers between the seaside and the yard side, and the corresponding route adoption. Meanwhile the SAP refers to the allocation of storage locations for the import containers, which are discharged from incoming vessels. These two aspects are known to be among the most critical terminal operations as they directly influence the efficiency of terminals (Ng *et al*., 2007). For example, any delay of transporting an export container from the yard side to the quayside for the uploading operation will cause a delay in the vessel's departure. This must be avoided. Similarly, an inadequate storage plan will induce a long transportation time, and overload certain QCs while idling others (Zhang *et al*., 2002; Sharif and Huynh 2002). Regarding the interaction of the SAP and YTS, it is necessary to study these two aspects as a whole. With the objective of finding proper storage locations for import containers and good schedules for dispatching yard trucks, a hybrid genetic algorithm (GA) is proposed to deal with the integrated approach.

This chapter is organized as follows. Section 4.2 describes the problem under investigation. In section 4.3, an MIP for YTS-SAP is developed. To solve the MIP, a GA is developed for solution in section 4.4. To test the proposed GA and verify the model, computational experiments are analyzed in section 4.5. Finally, section 4.6 concludes the chapter.

4.2 Problem Description

The problem is how to schedule a fleet of trucks to load or discharge all the containers and determine the storage location for the discharging containers. First of all, the transportation from a container's origin to destination is defined as a request, denoted by *i* and *j*. There are two types of requests considered in this study: loading requests and discharging requests. For a loading request, the origin is the location where a container is loaded onto a truck by a yard crane from a storage block in the yard side, while the destination is the location where a container is loaded onto the vessel by a QC. For an unloading request, the origin is the location where a container is unloaded from a vessel by a QC, while the destination is the location where a container is unloaded from a truck to a storage block by a yard crane in the yard side as in Figure 4.1.

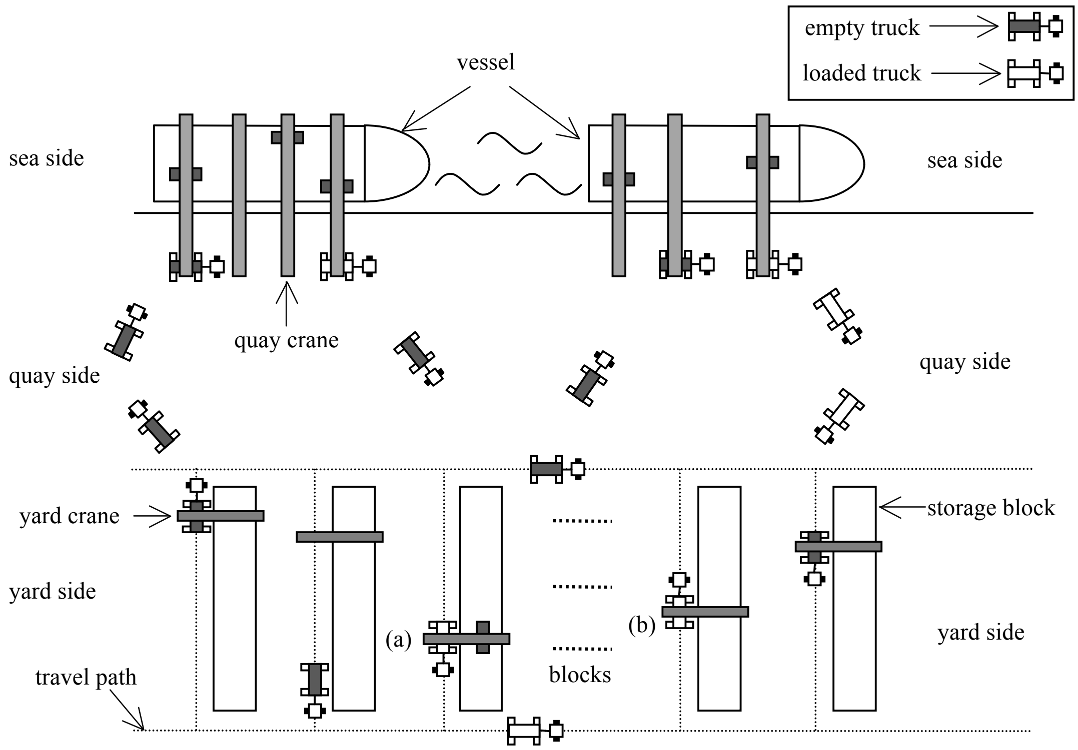

Figure 4.1 Outline of a container terminal

In terminal practice, a soft time window for each request $[a_i,b_i)$ is already pre-determined by the terminal operator as given data for YTS. The soft time window is a period of time involving the earliest possible time a_i and the due time b_i.

A container can only be handled no earlier than the earliest possible time and b_i can be viewed as a penalty. The processing time (loaded travel time) t_i is defined as the period of time that a truck processes a request i from its origin to its destination, and the setup time (empty travel time) s_{ij} is the period of time that a truck spends from the destination of the current request i to the origin of next request j. The starting time w_i of request i is defined as the time when it starts, and the completion time c_i of request i is the time when it finishes. The difference between the completion time c_i and b_i of request i is the delay of request i. Completion time of request i is: $c_i = w_i + t_i$. Delay of request i is: $d_i = \max\{0, c_i - b_i\}$. If request j is the successive request of request i served by the same truck, the starting time of request j is: $w_j = \max\{ w_i + t_i + s_{ij}, a_j \}$

4.3 Model Formulation for the YTS-SAP

The objective of the proposed model is the minimization of the summation of delay and yard trucks travel time. The output of the model is the yard truck transport schedules and storage location assignment for incoming containers.

The following assumptions are made in this study:

(1) There are limited numbers of trucks and one truck serves only one route.

Dummy requests l_r and k_r represent the initial and finial status of each route.

(2) The trucks travel between any pair of locations along the shortest and same path, so the travel times are symmetric. For example, in Figure 4.1, the truck travels from location (a) to location (b) and back along the same and shortest travel path.

(3) The number of storage locations is no less than the number of discharging containers.

(4) The yard crane and quay crane can serve the yard truck once the yard truck arrives at the yard crane or quay crane. This means that the yard crane and quay crane are always available.

(5) Congestion among yard trucks on a guide route are not considered.

The following notations are used in this study.

Indices:

i, j	Index of request, $i \neq j$.
r	Index of route.
p, q	Index of location.

k Index of storage location.

Problem data:

$\tau_{p,q}$ Travel time between location p to location q.

o_i Origin of request i.

e_i Destination of request i.

ζ_k Location of storage location k.

α_1 Weighting of delay.

α_2 Weighting of travel time.

Set of indices:

J^- Set of discharging requests with cardinality of $|J^-| = n^-$.

J^+ Set of loading requests with cardinality of $|J^+| = n^+$.

J Set of all requests, $J = J^- \cup J^+$, with cardinality of $|J| = n$.

$J^{'}$ Union set of all requests and initial status, $J^{'} = J \cup \{l_r\}$

$J^{''}$ Union set of all requests and final status, $J^{''} = J \cup \{k_r\}$.

R Set of routes, $|R|$ = m.

M Set of locations of the loading containers.

N Set of locations of the discharging containers.

K Set of the storage locations.

L Union set of the locations of the loading containers, the locations of the discharging containers and the storage locations. $L = M \cup N \cup K$.

Decision variables:

x_{ik} = 1, if container i is allocated to storage location k.

= 0, otherwise.

y_{ij} = 1, if request i is connected to request j in the same route.

= 0, otherwise.

w_i Starting time of request i.

c_i Completion time of request i.

d_i Delay of request i.

t_i Processing time of the yard trucks from the origin of request i to the destination of request i. $t_i = \tau_{oi,ei}$, if request i is a loading request; $t_i = \tau_{oi,\zeta k}$, if request i is a discharging request and allocated to storage location k.

s_{ij} Setup time of the yard trucks from the destination of request i to the origin of request j. $s_{ij} = \tau_{ei,oj}$, if request i is a loading request; $s_{ij} = \tau_{\zeta k,oj}$, if request i is a discharging request and allocated to storage location k.

The objective is to schedule the yard trucks and the allocation of the loading and unloading containers, aiming to minimize the summation of the delay of requests and the yard trucks travel time as modelled in equation (4.1).The model is as shown in the following:

Min: $Z = \alpha_1 \sum_{i \in J} d_i + \alpha_2 (\sum_{i \in J} t_i + \sum_{i,j \in J} s_{ij} y_{ij})$ (4.1)

Subject to the following constraints:

$$\sum_{i \in J^-} x_{ik} \leq 1 \quad \forall k \in K \tag{4.2}$$

$$\sum_{k \in K} x_{ik} = 1 \quad \forall i \in J^- \tag{4.3}$$

$$\sum_{j \in J''} y_{ij} = 1 \quad \forall i \in J' \tag{4.4}$$

$$\sum_{i \in J'} y_{ij} = 1 \quad \forall j \in J'' \tag{4.5}$$

$$w_i \geq a_i \quad \forall i \in J' \cup J'' \tag{4.6}$$

$$d_i \geq w_i + t_i - b_i \quad \forall i \in J' \cup J'' \tag{4.7}$$

$$w_j + M(1 - y_{ij}) \geq w_i + t_i + s_{ij} \quad \forall i \in J' \text{ and } \forall j \in J'' \tag{4.8}$$

$$t_i = \tau_{o_i, e_i} \quad \forall i \in J^+ \tag{4.9}$$

$$t_i = \sum_{k \in K} \tau_{o_i, \zeta_k} x_{ik} \quad \forall i \in J^- \tag{4.10}$$

$$s_{ij} = \tau_{e_i, o_j} \quad \forall i \in J^+ \text{ and } \forall j \in J \tag{4.11}$$

$$s_{ij} = \sum_{k \in K} \tau_{o_i, \xi_i} x_{ik} \quad \forall i \in J^- \text{ and } \forall j \in J \tag{4.12}$$

$$x_{ik}, y_{ij} \in \{0,1\}, \qquad \forall i \in J', \ \forall j \in J'' \text{ and } \forall k \in K \tag{4.13}$$

$$w_i \in \boldsymbol{R} \qquad \forall i \in J' \cup J'' \tag{4.14}$$

$$t_i \in \boldsymbol{R} \qquad \forall i \in J \tag{4.15}$$

$$s_{ij} \in \boldsymbol{R} \qquad \forall i \in J \text{ and } \forall j \in J \tag{4.16}$$

$$d_i \geq 0 \qquad \forall i \in J' \cup J'' \tag{4.17}$$

Constraints (4.2) ensure that each storage location will be assigned at most one discharging container. Constraints (4.3) ensure that each discharging container will be assigned one storage location. Constraints (4.4) ensure that $y_{ij} = 1$ if the yard truck processes request j after request i. Constraints (4.5) ensure that $y_{ij} = 1$ if the yard truck processes request i before request j. Constraints (4.6) ensure that requests can only be handled no earlier than the earliest possible time. Constraints (4.7) set the delay of every request. Constraints (4.8) give the connection of the starting time of a request and that of its successor. Constraints (4.9) calculate the travel time of the loading requests. Constraints (4.10) calculate the travel time of the discharging requests. Constraints (4.11) calculate the setup time of the loading requests. Constraints (4.12) calculate the setup time of the discharging requests. Constraints

(4.13) ensure that x_{ik} and y_{ij} are binary variables. Constraints (4.14) – (4.17) define the range of values for w_i, t_i ,s_{ij} and d_i.

One more decision variable l_{ij} is defined to linearize the nonlinear form in the objective, i.e. $s_{ij}\, y_{ij}$. Then the objective function can be rewritten as:

$$\text{Min: } Z= \alpha_1 \sum_{i \in J} d_i + \alpha_2 \left(\sum_{i \in J} t_i + \sum_{i,J \in J} l_{ij} \right) \qquad (4.18)$$

Three more constraints need to be added:

$$l_{ij} \geq y_{ij} + s_{ij} - 1 - M(1 - y_{ij}) \qquad \forall i \in J \text{ and } \forall j \in J \qquad (4.19)$$

$$l_{ij} \leq M \cdot y_{ij} \qquad \forall i \in J \text{ and } \forall j \in J \qquad (4.20)$$

$$l_{ij} \geq 0 \qquad \forall i \in J \text{ and } \forall j \in J \qquad (4.21)$$

Then the model can be modeled as a mixed integer linear programming with objective (4.18); subject to constraints (4.2) – (4.17) and (4.19) – (4.21)

4.4 Methodology for YTS-SAP

A hybrid GA is proposed for internal vehicle scheduling and storage space assignment problems.

4.4.1 Chromosome Representation

The chromosome represents a potential solution for internal vehicle scheduling and storage allocation. A gene represents a request, which contains the information of container ID, time window, origin and destination of the request, as shown in Table 4.1 and Figure 4.2. Each chromosome consists of $|J|+|R|$ genes. Each gene may be a positive number or a negative number. A positive number represents a request and the sequence of the request is prioritized from left to right. A negative number represents a route number. Moreover, the requests, which are between two successive negative genes, are allocated to the same truck.

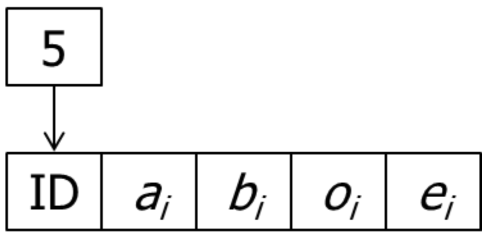

Figure 4.2 Example of chromosome representation

Table 4.1 Sample data of containers

Container ID	Origin	Destination	Time Window *a* (unit: second)	Time Window *b* (unit: second)	Type
1	(1035, 971)	(60, 665)	1362	1639	L
2	(108, 895)	(1464, 336)	716	1214	L
3	(359, 689)	(748, 1353)	284	634	L
4	(148, 391)	(1246, 312)	1320	1745	L
5	(800, 1180)	(113, 1287)	1201	1522	L
6	(767, 1015)	--	8	293	U
7	(496, 1210)	--	490	855	U
8	(1485, 414)	--	1160	1486	U
9	(99, 1440)	--	107	325	U
10	(130, 1498)	--	323	610	U

A chromosome of the proposed GA can be generated using the following steps.

Step 1: Randomly allocate different storage locations for each discharging request. Each gene contains information on the origin, destination and sequence of each request.

Step 2: Randomly allocate all negative number genes into the chromosome, and then the number of request in each route can be calculated.

Step 3: Randomly allocate all the requests to all the routes. The requests and the requests' sequence in each route can then be obtained.

Figure 4.3 is an example of a representation of the proposed GA for scheduling two yard trucks (|R| = 2) to process ten requests (|J| = 10) with a total length of |R| + |J| of a chromosome. The |J| requests are represented by a permutation of the integers from 1 to |J|. The |R| routes are represented by the integers from -|R| to -1. The decoding procedure is in the reverse order of encoding. In the example shown in Figure 4.3, the first yard truck would sequentially process requests 9, 6, 10, 7; the second truck would process requests 3, 2, 8, 5, 1, 4, as shown in Figure 4.4. As the sample data shown in Table 4.1 and Table 4.2, if the discharging container 8 is allocated to storage location 1, the second truck may travel the coordinates (359, 689), (748, 1353), (108, 895), (1464, 336), (1485, 414), (1039, 592), (800, 1180), (113, 1287), (1035, 971), (60, 665), (148, 391), (1246, 312) one by one.

Table 4.2 Sample data of storage locations for discharging containers

1	2	3	4	5	6	7
(1039,592)	(395,686)	(18,1263)	(635,357)	(143,789)	(113,1323)	(321,563)

Request	9	6	10	7	-1	3	2	8	5	1	4	-2
Sequence	1	2	3	4		1	2	3	4	5	6	
Truck	Truck 1					Truck 2						

Figure 4.3 Example of chromosome encoding

Route 1: $\boldsymbol{l_1 \rightarrow 9 \rightarrow 6 \rightarrow 10 \rightarrow 7 \rightarrow k_1}$

Route 2: $\boldsymbol{l_2 \rightarrow 3 \rightarrow 2 \rightarrow 8 \rightarrow 5 \rightarrow 1 \rightarrow 4 \rightarrow k_2}$

Figure 4.4 Decoding of chromosome illustrated in Figure 4.2

4.4.2 Generation of Initial Pool

In this study, the initial pool (with pool size P) is generated by heuristic rules and random generation. To increase the quality of the initial pool, one of the chromosomes is generated according to the earliest possible time, combining with the nearest storage location. One of the chromosomes will be generated by the earliest due time combined with the nearest storage location. The rest of the chromosomes are randomly generated.

4.4.3 Mating Pool and Elitist Strategy

The commonly used roulette wheel selection approach is applied for forming a mating pool. Furthermore, an elitist strategy is used to keep the best chromosome(s). The stored best chromosome found during the evolution will replace the chromosome with lowest fitness value.

4.4.4 Fitness Value

The objective is the minimization of the summation of the delay and the yard trucks travel time. Thus, the fitness value of a chromosome can be the reciprocal of its objective function value, as shown in Eq. (4.22). In this way, the best chromosome, which corresponds to the scheduling of the trucks and the allocation of the discharging containers with minimum summation of delay and travel time, can be found.

$$\text{Fitness} = 1 / Z \qquad (4.22)$$

4.4.5 Crossover Operation

Many studies (e.g. Blanton and Wainwright, 1993; Poon and Carter, 1995; Larrañaga *et al.*, 1999; Moon *et al.*, 2002) have shown that instance-specified information can make the GA searching process more effective. In the YTS-SAP, the instance-specified information is the request's earliest starting time, the request's due time, the request's processing time and setup time between the two requests. In the proposed GA, this instance-specified information tries to be inherited with the crossover operation. Consider the crossover operation of two parents P_1 and P_2 to reproduce two offspring O_1 and O_2. The procedure of the proposed crossover operation is shown in the following steps. Figure 4.5 shows an example of crossover and the example uses the data shown in Table 4.1.

Parent	P1	6	8	5	4	7	3	2	-1	1	9	10	-2
	P2	9	2	5	-1	10	1	4	3	6	7	8	-2
After first time	Ω_1	6	8	5	4	7	3	2	9				
step 2	Ω_2	6	8	5	4	7	3	2	9				
After second	Ω_1	1	4	10									
time step 2	Ω_2	1	2	4	5	7	8	10					
Offspring	O1	6	9	3	7	2	8	5	-1	10	4	1	-2
	O2	6	9	3	-1	10	7	2	8	5	1	4	-2

Figure 4.5 Example of crossover operation

Step 1: Add all the requests in route one of both parent P_1 and parent P_2 into empty requests set Ω_1. Delete the duplicated requests in Ω_1. Let set Ω_2 be the same as Ω_1.

Step 2: Rank the requests in Ω_1 in non-decreasing order of their earliest starting time and let set Φ be the ranked set. Rank the requests in Ω_2 in non-decreasing order of their due time and let set Ψ be the ranked set.

Step 3: Insert the requests in the corresponding route in O_1 according to their order in set Φ and delete the inserted requests from set Ω_1. Then, insert the requests in the corresponding route in O_2 according to their order in set Ψ and delete the inserted requests from set Ω_2.

Step 4: Add all the requests in the next route for both parent P_1 and parent P_2 into set Ω_1. Then, delete the duplicated requests and delete the requests that have been inserted in O_1. Add all the requests in the next route for both parent P_1 and parent P_2 into set Ω_2. Then, delete the duplicated requests and delete the requests that have been inserted in O_2.

Step 5: Repeat step 2-4 until all the routes are assigned.

4.4.6 Fine Local Searching

To make the GA converge faster and be steadier, an exhaustive heuristic method (Chung *et al.*, 2011; Palpant *et al.*, 2001) is adopted. The exhaustive heuristic method is used to reinforce the GA's local searching ability. In one part of a chromosome, a set of continuous genes is selected as a segment and the number of genes formed in the segment is set to be 5, as adopted by Chung *et al*. (2011). This method is adopted in each chromosome part, such that each chromosome for each of the trucks in the exhaustive searching process will be executed once. Taking the chromosome shown in Figure 4.3 as an example, the first part of the chromosome contains four genes that are not enough to form a segment, and so local searching will not be employed for the first part of the chromosome. However, if the genes 2, 8, 5, 1 and 4, which are in the second part of the chromosome, are randomly selected as a segment, all combinations of the containers sequences will be tested, and the one with the best fitness value will be recorded.

4.4.7 Mutation Method (1) – Simple Mutation Operation

The mutation operation can help the GA prevent premature convergence and find the global optimal solution. In order to evaluate the performance of the proposed hybrid GA, a simple GA is used as a comparison. This proposed simple GA will use the simple mutation operation. In the proposed simple GA, each chromosome contains three types of information: storage locations of the discharging containers, the sequence of requests in each route, and the amount of requests in each route. Thus, each chromosome can be mutated in three ways. The first method is to randomly choose a discharging request and change the request's storage location to another empty storage location. The second method is to randomly select two positions and then swap the requests on these positions; Figure 4.6 shows how gene 7 and gene 9 are swapped. The third method is to change the amount of requests in the two routes, randomly selecting a request in a truck and inserting the request in another truck; Figure 4.7 shows how gene 7 is inserted between gene 9 and gene 10. Each of the three mutation methods is applied once during one mutation operation.

P1	6	8	5	4	7	3	2	-1	1	9	10	-2
O1	6	8	5	4	9	3	2	-1	1	7	10	-2

Figure 4.6 Example of mutation of the second way

P1	6	8	5	4	7	3	2	-1	1	9	10	-2
O1	6	8	5	4	3	2	-1	1	9	7	10	-2

Figure 4.7 Example of mutation of the third way

4.4.8 Mutation Method (2) – Mutation Ways with Guidance

In the proposed hybrid GA, new mutation ways with guidance instead of the simple mutation methods are adopted. During the mutation of the storage location, a discharging request is first randomly selected and then all the storage locations at which the request's travel time is within the request's due time are selected as a set; Figure 4.8 shows storage location 1, 2 and 3 as an example. Finally, a storage location is randomly chosen in the set to replace the original storage location.

For the mutation method of changing the position of two requests, a request is randomly selected in one truck, recording the position m of the request. Then, randomly select another request in the range of m + n to m – n in another truck, where n is a positive integer. Finally, swap these two requests. Figure 4.9 is an example of this guidance mutation method where request 10 is selected to swap with another request. As request 10 is the third request in the first part of the chromosome, m is equal to 3. If n is set to be 2, another request is randomly selected between request 3 and request 1. In this study, n is set to be 3.

For the mutation method of changing the amount of requests in the two trucks, a request is randomly selected in one truck, recording the position m of the request. The request is then inserted in the range of m + n to m – n in another truck, where n is a positive integer. Figure 4.10 is an example of this guidance mutation method, where request 10 is selected to swap with another request. As request 10 is the third request in the first part of the chromosome, m is equal to 3. If n is set to be 2, request

10 is randomly inserted between request 3 and request 1. In this study, n is set to be 3 in order to avoid a large change of chromosomes. The details of the proposed hybrid GA are as shown in Figure 4.11.

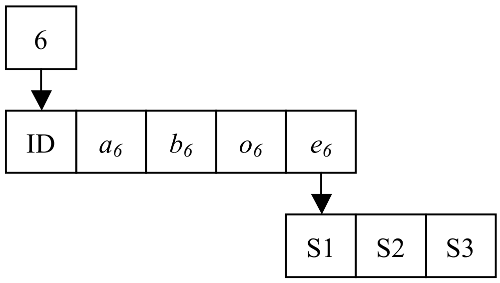

Figure 4.8 Example of guidance mutation method one

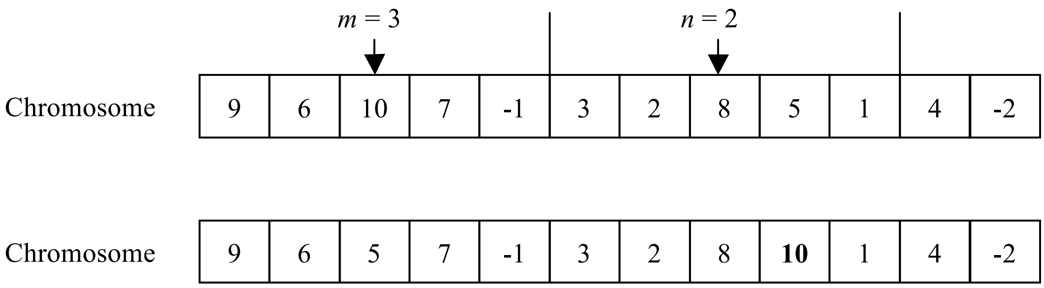

Figure 4.9 Example of guidance mutation method two

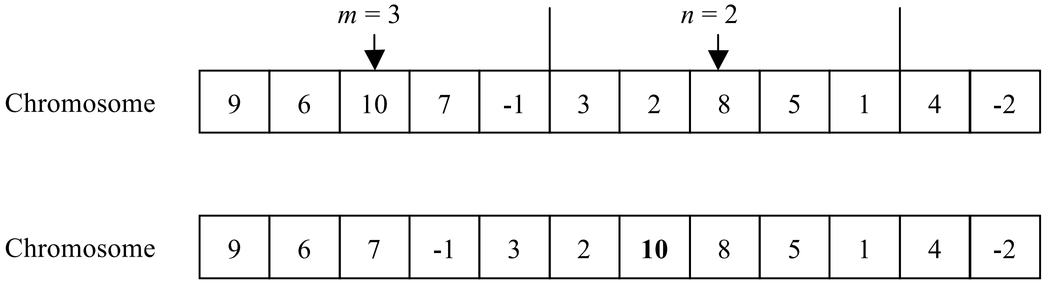

Figure 4.10 Example of guidance mutation method three

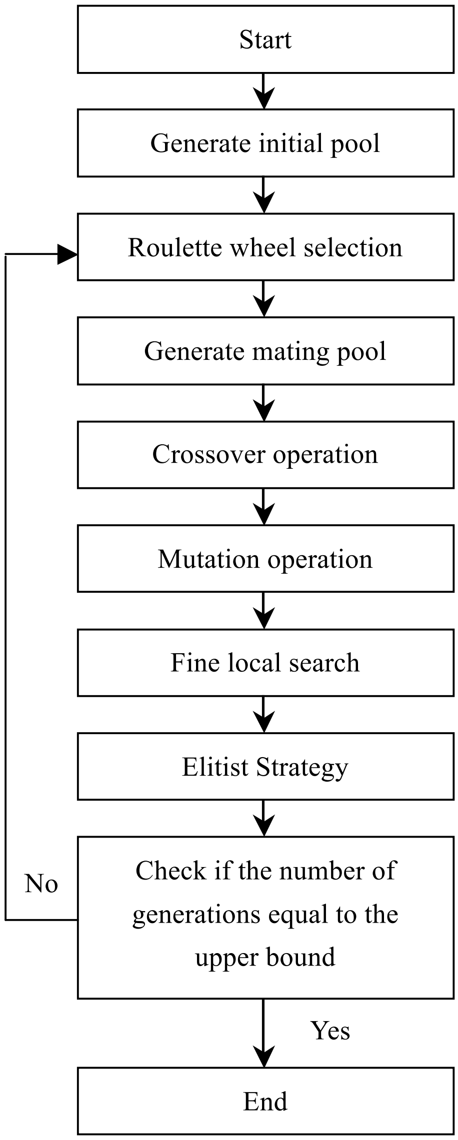

Figure 4.11 Flowchart of the proposed GA

4.5 Computational Experiments

To evaluate the quality of the proposed GA, a number of computational experiments are used to test the performance of the proposed GA. The GA is coded by using Java Language and executed on a PC with Intel Core i7 3.4 GHz and 8 GB RAM. Instances used in the experiments are created according to the following criteria:

(1) The origin and destination of the loading containers, the origin of the discharging containers and the storage locations are created following a uniform distribution in the two-dimension square space from $0*0m^2$ to $1500*1500\ m^2$.

(2) The earliest possible time of the requests is randomly generated following a uniform distribution of U (0, 1500) (unit: second) and the due time of requests is generated following a uniform distribution of U (200, 500) (unit: second).

(3) The traveling speed of yard trucks is 11.11 m/s (40 km/h).

The two weight parameters α_1 and α_2 are set to have the relation of $\alpha_1 + \alpha_2 = 1$ and set α_1 equal to 0.6, as described by Lee *et al*. (2009).

4.5.1 Small Scale Problems

For small-scale problems, a simple GA, which is the hybrid GA without exhaustive heuristic and guidance mutation, is used for comparison with the MIP model solved by CPLEX. The parameters of the simple GA are set as: population size: 10; crossover rate P_C 0.8, mutation rate P_M 1, and the maximum number of generations is 2000. The number of routes is set as two. The hybrid GA is also compared with the MIP model solved by CPLEX. The parameters of the hybrid GA are the same as the simple GA except that the maximum number of generations is set to 200. Table 4.3(a - c) shows an example of input data, which contains the information on loading jobs, unloading jobs, and storage locations.

Table 4.3a Input data on loading jobs of experiment 10 in small scale case

ID	Origin	Destination	Time window
1	(327, 1465)	(567, 444)	(1407, 1660)
2	(458, 333)	(858, 957)	(614, 967)
3	(525, 1231)	(296, 360)	(922, 1268)
4	(450, 241)	(533, 444)	(1214, 1491)
5	(211, 434)	(1020, 1301)	(91, 456)

Table 4.3b Input data on unloading jobs of experiment 10 in small scale case

ID	Origin	Time window
1	(674, 73)	(1339, 1557)
2	(1436, 223)	(716, 1017)
3	(1408, 886)	(518, 981)
4	(819, 1313)	(612, 1080)
5	(460, 181)	(289, 591)

Table 4.3c Input data on storage locations of experiment 10 in small scale case

ID	Coordinates of storage locations
1	(1130, 438)
2	(1188, 91)
3	(687, 13)
4	(767, 1170)
5	(730, 534)
6	(1006, 1327)
7	(90, 758)
8	(448, 517)
9	(142, 1286)
10	(1369, 1179)

As shown in Table 4.4, the simple GA can obtain the optimal solution in reasonable time in the first four cases. Due to interaction of the yard truck scheduling problem and storage allocation problem, CPLEX requires hours to solve each single instance, whereas the simple GA uses only a few seconds to obtain a solution. For the last six instances, the simple GA can obtain the near optimal solution and the average gap between the simple GA and the optimal solution obtained by Branch and Bound coded in CPLEX is computed at about 4.35%. With the size becoming larger, the gap also becomes larger. The simple GA performs poorly with increasing instance size. However, the performance of the simple GA is acceptable from the practical point of view. On the other hand, the hybrid GA can always obtain optimal solutions because of guidance mutation and the exhaustive heuristic for local searching. As the maximum number of generations is smaller than the simple GA, the hybrid GA is faster than the simple GA in the first six instances. However, the hybrid GA needs more time than the simple GA when the instance scale becomes larger.

Table 4.4 Computational results of random instances in small scale

Experiment No.	Size(loading×discharging×storage locations)	CPLEX		Simple GA		Gap(%) between CPLEX and Simple GA	Hybrid GA		Gap(%) between CPLEX and Hybrid GA
		Value	CPU(s)	Value	CPU(s)		Value	CPU(s)	
1	3×3×3	177.6	7.77	177.6	3.11	0	177.6	1.83	0
2	3×3×5	157.2	27.31	157.2	2.97	0	157.2	2.01	0
3	4×4×4	209.6	148.22	209.6	3.53	0	209.6	2.61	0
4	4×4×5	209.6	7133.48	209.6	3.67	0	209.6	2.60	0
5	5×4×4	214	46350	218.5	3.70	2.1%	214	3.17	0
6	5×5×5	283.6	97612	292.4	3.81	3.1%	283.6	3.64	0
7	7×5×5	372.6	18935	384.6	3.86	3.2%	372.6	4.10	0
8	7×7×9	365	*	382.2	4.04	4.7%	365	4.78	0
9	9×7×10	385	*	406.9	4.27	5.7%	385	4.95	0
10	10×10×20	443.5	*	476.1	4.38	7.3%	443.5	5.59	0
* The computational time is longer than 10 hours.									

4.5.2 Large Scale Problems

To evaluate the performance of the proposed hybrid GA in large scale applications, the simple GA is applied for comparison with the hybrid GA. Table 4.5 gives partial input data of 100 containers with uniform distribution for both earliest possible time and due time.

Four different kinds of distribution combinations of the earliest possible time and the due time are applied as the criteria for generating instances. The number of available trucks is also changed. The number of trucks is set as 3 at first, and then the number of trucks is set as 6 for the fifth kind of criteria. Using each of the five criteria forms three different kinds of instances with different sizes. The criteria of the instances are created as shown in Table 4.6 and Table 4.7. An example of 100 containers' information can be found in Appendix 1. The parameters of the proposed hybrid GA for large scale are set as: population size 10, crossover rate P_C 0.8, and mutation rate P_M 0.9. Table 4.8 also shows the number of generations, which is long enough to attain a steady solution, and the computational time of the GA. As shown in Table 4.8 and Table 4.9(a-c), the proposed hybrid GA can obtain the best results, and the computational time is a little longer than the simple GA.

Table 4.5 Partial input data of 100 containers with uniform distribution for both earliest possible time and due time

ID	Origin	Destination	Time window	Type
1	(175, 993)	(1057, 1296)	(655, 917)	L
2	(590, 803)	(54, 1270)	(525, 830)	L
3	(1371, 1490)	(1392, 812)	(86, 433)	L
4	(217, 734)	(283, 299)	(297, 662)	L
5	(400, 397)	(1267, 80)	(98, 450)	L
6	(1110, 983)	(811, 831)	(1090, 1467)	L
7	(1247, 250)	(634, 816)	(1026, 1362)	L
8	(1149, 932)	(189, 154)	(187, 527)	L
91	(24, 794)	---	(1079,1570)	U
92	(1376, 485)	---	(509, 954)	U
93	(635, 1376)	---	(1329, 1608)	U
94	(506, 1393)	---	(202, 435)	U
95	(292, 1039)	---	(69, 345)	U
96	(882, 526)	---	(926, 1242)	U
97	(258, 502)	---	(463, 763)	U
98	(329, 604)	---	(133, 337)	U

Table 4.6 Number of containers and storage locations used in the instances

	No. of loading containers	No. of discharging containers	No. of storage locations
100 containers	60	40	100
200 containers	100	100	140
300 containers	160	140	200

Table 4.7 Criterion of generating earliest possible time and due time for instances in large scale

No. of distributions	Earliest possible time	Due time
1	Uniform distribution	Uniform distribution
2	Normal distribution	Uniform distribution
3	Exponential distribution	Uniform distribution
4	Uniform distribution	Normal distribution

Table 4.8 Computational time and generation GA used

	Simple GA		Hybrid GA	
	CPU(s)	Generation	CPU(s)	Generation
100 containers	22	10000	74	1000
200 containers	178	30000	228	1300
300 containers	375	60000	382	1500

In this research, the gap of the proposed hybrid genetic algorithm and other approaches is calculated. An example of the deviation between heuristic method one and the hybrid genetic algorithm is as follows:

$$gap\% = \frac{(result\ of\ heuristic\ method\ one) - (result\ of\ proposed\ hybrid\ GA)}{result\ of\ heuristic\ method\ one} \qquad (4.23)$$

The lowest gaps between the simple GA and the new hybrid GA are 1%, 1%, and 3%, respectively for 100 containers, 200 containers and 300 containers. The highest gaps between the simple GA and the new hybrid GA are 35%, 44%, and 17%, respectively for 100containers, 200containers and 300containers. The average gaps between the simple GA and the hybrid GA are 11%, 11%, and 7%, respectively for 100containers, 200containers and 300containers. Since the hybrid GA has stronger local search ability and the mutation operation is not totally random, the results of the hybrid GA are better than the simple one. However, the exhaustive heuristic is time consuming and it takes the hybrid genetic more time to find a solution.

Table 4.9a Computational results of random instances of 100 containers

No. of containers	Criteria of forming instances	Simple GA	Hybrid GA	Gap (%)
100 containers	1	3432.4	3230.2	5%
	1	2836	2695.2	5%
	1	2997.8	2886.8	4%
	2	3470.4	2604.4	25%
	2	3997.2	3639.6	9%
	2	5752.8	5032	12%
	3	6206	5407.2	13%
	3	12239.2	11110.8	9%
	3	11013.2	8122.6	26%
	4	4507.4	2945.2	35%
	4	2916.8	2709.2	7%
	4	3068	2933.4	5%
	5	2740	2660.4	3%
	5	2665.6	2637.4	1%
	5	2857.2	2757.4	3%

Table 4.9b Computational results of random instances of 200 containers

No. of containers	Criteria of forming instances	Simple GA	Hybrid GA	Gap (%)
200 containers	1	24863.6	21566.8	13%
	1	42080.2	35506	16%
	1	29926.6	26421.2	12%
	2	50892	50875.2	1%
	2	54559.4	51487.2	6%
	2	51953.2	47241.6	9%
	3	57543	50917.2	12%
	3	75370	60192.8	20%
	3	52303.6	41523.6	21%
	4	30470.6	16952.4	44%
	4	36708.8	34962.2	5%
	4	34427.4	32031.6	7%
	5	4893.8	4645.4	5%
	5	4861.8	4812.4	1%
	5	5020	4943.4	2%

Table 4.9c Computational results of random instances of 300 containers

No. of containers	Criteria of forming instances	Simple GA	Hybrid GA	Gap (%)
300 containers	1	120613	117577.6	3%
	1	159931.2	151825.8	5%
	1	152231.4	145829	4%
	2	140016	133199.8	5%
	2	128797.2	123056.2	4%
	2	151134	141434.6	6%
	3	181894.6	174253.6	4%
	3	183754	176955.8	4%
	3	200072.8	191379.6	4%
	4	149158.6	123718.8	17%
	4	154976.8	143830.8	7%
	4	155862	151624	3%
	5	11003.4	9864.6	10%
	5	19459.8	18050	7%
	5	20005.4	16538.2	17%

4.6 Summary

Internal vehicle scheduling and storage location assignment are two essential issues for container terminals to successfully deal with in order to enhance operational efficiency. Based on previous studies, the existing model has been improved by considering the situation in which the number of available storage locations is not equal to the number of import containers. Such improvement can make the model more practical. As the problem complexity increases dramatically, a new hybrid GA with exhaustive heuristic and guidance mutation is proposed. The crossover operation of proposed GA is based on the information of a request's ready time and due time. The mutation operator combines three new mutation approaches. To evaluate and demonstrate the quality of the proposed hybrid GA, both a simple GA and the hybrid GA are compared with the MIP model solved by CPLEX for small-scale problems, and then the proposed hybrid genetic is compared with the simple GA by using large-scale instances. It is proven that the simple GA and the hybrid GA can obtain near optimal solutions in reasonable time by using a series of computational experiments for small-scale problems. For large-scale problems, 100, 200 and 300 containers with different numbers of storage locations and trucks are studied. The results demonstrate that the proposed hybrid GA can obtain the best solutions compared to the simple GA method.

In this chapter, the number of vehicles and storage locations are assumed to be known. Given this information, yard truck routing and storage location for discharging containers are determined. However, in practical situations, the number of trucks can be flexible and the number of storage locations may dynamically change throughout the operating horizon. Therefore, the number of trucks and storage locations can be considered as variables in future work. In the next chapter, the influence of yard truck configuration on yard truck scheduling and storage location assignment is described.

Chapter 5 Integration Problem of Storage Space Assignment, Yard Truck Scheduling and Yard Truck Deployment Strategy in Gateway Container Terminals

5.1 Introduction

In the previous chapter, how to assign storage locations for incoming containers and schedule yard tucks to perform transport jobs are described as integration. The integrated problem is a common problem in traditional container terminals. This chapter further studies the integrated problem by considering more practical issues in container terminals, i.e. yard truck deployment strategy.

Container throughput fluctuation always occurs, even in a mature port, such as Hong Kong Port, as shown in Figure 5.1, and also in fast developing ports, such as Shanghai Port and Shenzhen Port. As demand fluctuation is common to terminal industries, keeping a full fleet of trucks to meet all the internal transportation requirements is not economical (Petering, 2011). In addition, employing a large number of trucks not only costs extra money, but may also result in traffic congestion (Angeloudis and Bell, 2010). Studying the influence of container throughput fluctuation during a significant period of time (e.g. one year) on yard truck deployment strategies is a necessity for the container terminal industry, since terminal companies need to decide on yard truck deployment strategies based on the container throughput data. A good way to overcome truck deployment difficulties is to allow some internal trucks to be rented from external companies, as has been done in Hong Kong terminals.

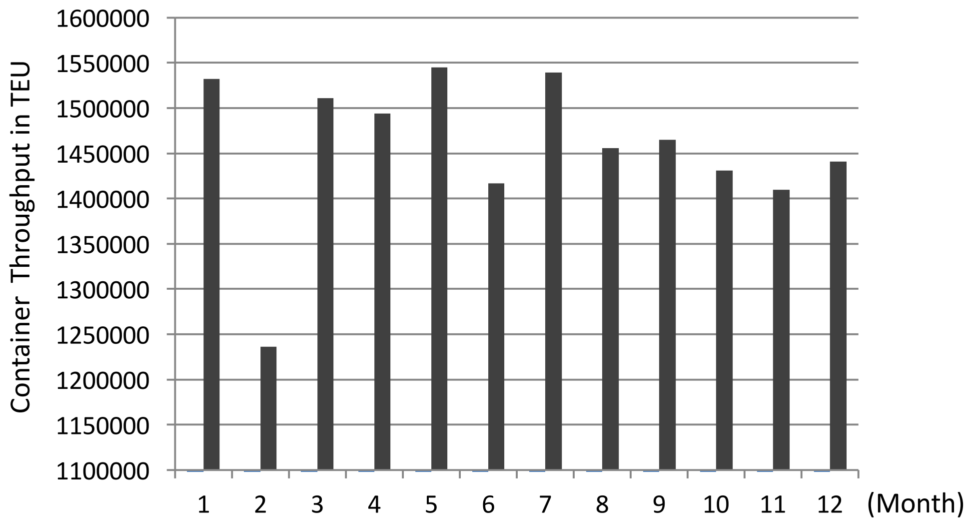

Figure 5.1 Container throughput of Hong Kong Port in the year 2012
(source: Port and Maritime Statistics of Marine Department of Hong Kong, 2014)

New decision issues appear when container terminals rent internal trucks, since the cost of owning and renting trucks are different. One issue is to decide on the number of trucks that should be owned, which is regarded as a long-term strategic decision. This is because owning too many trucks requires a big capital investment and renting additional trucks is expensive. Another issue is how many trucks should be rented each day to meet the daily transportation requirement with a satisfactory performance level. Both of these issues are closely related to the productivity and efficiency of terminals. This study is intended to fill the research gap in the determination of strategies for employing internal trucks to meet daily operational transportation requirements and to minimize long-term costs.

This chapter is organized as follows: section 5.2 provides a general description; a mathematical model is developed in section 5.3; section 5.4 presents the proposed heuristic algorithm; section 5.5 presents the computational experimental results; and section 5.6 provides a summary.

5.2 General Description

This research studies the strategy of using rented and owned internal trucks to handle a number of import and export containers. When a vessel berths at a port, loading and unloading operations should be finished before the scheduled departure time. Similarly, in the terminal, a container should be delivered to an external truck on time or risk the imposition of a penalty. However, a penalty caused by late delivery is difficult to calculate and the inherent complexity makes it difficult to solve. Also, in practice, container terminals are fined a large amount of money for any penalty; thus, terminal operators try to prevent delay, even if more internal trucks are needed. It is thus assumed that container terminal operators do not allow delays to occur.

In a given time horizon, e.g. one year, R is a set of days, indexed by r. To transport containers, owned and rented internal trucks are used every day. The number of owned internal trucks H is a decision variable. The owned internal trucks are always available to transport containers, and the number of owned internal trucks H_r used on day r, is also a decision variable. In addition, the number of rented internal trucks employed on day r is defined as S_r. Then, the total number of internal trucks employed on day r is $T_r = H_r + S_r$.

Normally, the number of import and export containers is different each day. So, on day r, let N_r be the set of containers, with N_r^+ the set of export containers and N_r^- the set of import containers, with cardinalities of n_r, n_r^+, n_r^-, respectively. Let i or j denote a container. The storage spaces in the yard side also change each day, so let M_r be the set of storage spaces available for storing import containers on day r, with cardinality of m_r. Then, the set of all the containers Z within the given time horizon is: $Z = N_1 \cup N_2 \cup \cdots \cup N_{|R|}$.

At a vessel berth-in, a soft time window $[a_i, b_i)$ for each container is given to each container based on the crane schedules. A container cannot be handled before the earliest possible time a_i, and a container handled beyond the due time b_i is delayed. Let container i start to be served at starting time c_i, and completed at completion time f_i. The container delay i is:

$$d_i = \max\ \{0, f_i - b_i\}. \tag{5.1}$$

It is assumed that the processing time w of the quay and yard cranes for a container is identical and a known constant. Each container should be loaded/unloaded by both quay cranes and yard cranes, thus an internal truck is needed to wait for the processing time $2w$ when the truck is handling a container. The time lapse to process container i from the origin to the destination is defined as the processing time p_i of container i. The travel time of the empty trip between two successive containers i and j as the setup time q_{ij} of the two containers is also defined. Then, the procedure of a truck processing container j after container i will be as follows: firstly, the truck leaves container i and makes an empty trip to the origin of container j; then the truck waits for the quay/yard crane to handle container j; this truck then travels from the origin of container j to the destination of container j; finally, the truck waits for the yard/quay crane to process container j and then leaves for the next container. Therefore, the relation between the starting time c_i of container i and the starting time c_j of container j is: $c_j = \max\ \{ c_i + w + p_i + q_{ij} + w, a_j \}$.

The processing time p_i of container i includes two conditions. If container i is an export container, p_i is a known constant since the origin and destination of container i are predetermined. On the other hand, if container i is an import container, p_i is determined by the storage location allocated to container i. Similarly, the setup time q_{ij} of two successive containers i and j also encounters two situations. If container i is an export, q_{ij} is a known constant as the destination of container i and the origin of container j are prearranged. In addition, if container i is an import container, q_{ij} is also determined by the storage location allocated to container i.

It is assumed that congestion and blockage problems of internal tractors are not considered. This assumption follows that of other researchers, such as Vis *et al.* (2005), Cao *et al.* (2008), Lee *et al.* (2009) and Lee *et al.* (2010), since the congestion and blockage problem will greatly complicate the model and make it hard to formulate as a linear mathematical model. Two dummy jobs are added, l_s and l_f, as the initial and final status of the T_r internal trucks. The dummy jobs can be taken as the parking area or rest area. Let $N_r{}'$ be the set of $N_r \cup l_s$ and $N_r{}''$ be the set of $N_r \cup l_f$. Each truck travels from l_s to l_f and transports a series of containers sequentially. A feasible sequence of containers is then the route that an internal truck will travel.

5.3 Mathematical Model

The following notations are used in this chapter:

Indices

g,k Index of locations.

r Index of days.

i, j Index of containers.

Sets

R Set of days.

N_r Set of all containers on day r.

N_r^+ Set of import containers on day r.

N_r^- Set of export containers on day r.

N_r' Set of all containers and initial status.

N_r'' Set of all containers and finial status.

M_r Set of all available storage locations on day r.

Problem data

a_i Earliest possible time of container i.

b_i Due time of container i.

w Processing time of containers using either quay cranes or yard cranes.

$\tau_{g,k}$ Travel time between each pair of locations (g,k).

o_i Origin of container i.

e_i Destination of export container i.

φ_{mr} Location of storage location m_r.

α_1 Cost of owning an internal truck.

α_2 Cost of using an owned yard truck per day.

α_3 Cost of using an rented yard truck per day.

α_4 Cost of delay per time unit.

p_i Processing time of export container i.

q_{ij} Setup time of two successive containers i and j, container i is an export container.

Decision variables

T_r Number of internal trucks employed on day r.

c_i Starting time of container i.

f_i Completion time of container i.

d_i Delay of container i.

p_i Processing time of import container i.

q_{ij} Setup time of two successive containers i and j, container i is an import container .

x_{imr} = 1, if container i is allocated to storage location m_r.

= 0, otherwise.

y_{ij} = 1, if container j is served immediately after container i by the same truck.

= 0, otherwise.

H Number of internal trucks owned by a container terminal.

S_r Number of internal trucks rented on day r by a container terminal.

H_r Number of owned internal trucks H_r used on day r by a container terminal.

Objective function:

Minimize: $$\Delta = \alpha_1 H + \alpha_2 \sum_{r\in R} H_r + \alpha_3 \sum_{r\in R} S_r + \alpha_4 \sum_{i\in Z} d_i \tag{5.2}$$

Subject to:

$$\sum_{i\in N_r^-} x_{im_r} \le 1 \qquad \forall\, m_r \in M_r \tag{5.3}$$

$$\sum_{m_r\in M_r} x_{im_r} = 1 \qquad \forall\, i \in N_r^- \tag{5.4}$$

$$\sum_{j\in N_r''} y_{ij} = 1 \qquad \forall\, i \in N_r \tag{5.5}$$

$$\sum_{i\in N_r'} y_{ij} = 1 \qquad \forall\, j \in N_r \tag{5.6}$$

$$\sum_{j\in N_r} y_{ij} = H_r + S_r \qquad \forall\, r \in R \text{ and } i = l_s \tag{5.7}$$

$$\sum_{i \in N_r} y_{ij} = H_r + S_r \qquad \forall\, r \in R \text{ and } j = l_f \tag{5.8}$$

$$H_r + S_r = T_r \qquad \forall\ r \in R \tag{5.9}$$

$$T_r \geq H_r \qquad \forall\ r \in R \tag{5.10}$$

$$T_r \geq S_r \qquad \forall\ r \in R \tag{5.11}$$

$$H \geq H_r \qquad \forall\ r \in R \tag{5.12}$$

$$c_i \geq a_i \qquad \forall\, i \in N_r \tag{5.13}$$

$$d_i \geq c_i + w + p_i + w - b_i \qquad \forall\, i \in N_r \tag{5.14}$$

$$c_j + K(1 - y_{ij}) \geq c_i + w + p_i + w + q_{ij} \qquad \forall\, i, j \in N_r \quad \text{and } i \neq j \tag{5.15}$$

$$p_i = \tau_{oi,\, ei} \qquad \forall\, i \in N_r^{+} \tag{5.16}$$

$$p_i = \sum_{m_r \in M_r} \tau_{oi,\, \varphi m_r} x_{im_r} \qquad \forall\, i \in N_r^{-} \tag{5.17}$$

$$q_{ij} = \tau_{ei,\, oj} \qquad \forall\, i \in N_r^{+} \text{ and } j \in N_r \tag{5.18}$$

$$q_{ij} = \sum_{m_r \in M_r} \tau_{\varphi m_r,\, oj} x_{im_r} \qquad \forall\, i \in N_r^{-} \text{ and } j \in N_r \tag{5.19}$$

$$x_{im_r}, y_{ij} \in \{0,1\}, \qquad \forall\, i \in N_r{'}, j \in N_r{''} \text{ and } m_r \in M_r \tag{5.20}$$

$$c_i, d_i \in \mathbf{R} \qquad \forall\, i \in N_r{'} \cup N_r{''} \tag{5.21}$$

$p_i \in \mathbf{R}$ $\quad \forall\, i \in N_r^-$ (5.22)

$q_{ij} \in \mathbf{R}$ $\quad \forall\, i \in N_r^-$ and $j \in N_r$ (5.23)

$H,\, H_r,\, S_r \in \mathbf{R}$ (5.24)

Constraints (5.3) ensure that one storage location can store one container at most. Constraints (5.4) ensure that each container can only be assigned to one storage location. Constraints (5.5) and (5.6) form a feasible sequence of two containers on one route. Constraints (5.7) and (5.8) set the number of trucks needed each day. Constraints (5.9) – (5.11) set the number of internal trucks employed each day. Constraints (5.12) set the number of in-house maintained internal trucks. Constraints (5.13) ensure that a container can only be handled no earlier than the earliest possible time. Constraints (5.14) set the delay of every container. Constraints (5.15) give the connection between the completion time of a container and the starting time of the next. Constraints (5.16) and (5.17) set the processing time of each container. Constraints (5.18) and (5.19) calculate the empty travel time between two successive containers. Constraints (5.20) – (5.24) are the domain constraints of the decision variables.

5.4 A Heuristic Algorithm

The problem of scheduling internal trucks and the allocation of storage locations for import containers each day can be reduced to the YTS-SAP, which is an NP-hard problem, proven by Lee *et al*. (2009) who not only considered the scheduling of internal trucks and storage allocation each day, but also studied the strategy of employing two types of internal trucks during a long planning horizon. These two issues can be viewed as a daily decision problem and a long-term planning problem. As these two problems are not independent of each other, it is very difficult to find the solutions simultaneously. Meta-heuristics are known to be appropriate approaches to this problem and have been widely applied in different models by many researchers. Therefore, a heuristic approach will also be applied here for the solution of assignment and scheduling yard trucks for every day. Among all the meta-heuristic approaches, the GA will be one of the options as there are many successful cases using GA that can be followed (Ng. *et al.*, 2007; Lee *et al.*, 2010; Chung *et al*., 2011). A two-level heuristic (TLH) method is used for the solution. In the first level, the scheduling of internal trucks and the storage allocation for every single day is firstly studied by using a hybrid genetic algorithm (GA). In the second level, the long-term deployment strategy of the internal trucks is determined by using linear programming. The workflow of the proposed TLH is shown in Figure 5.2.

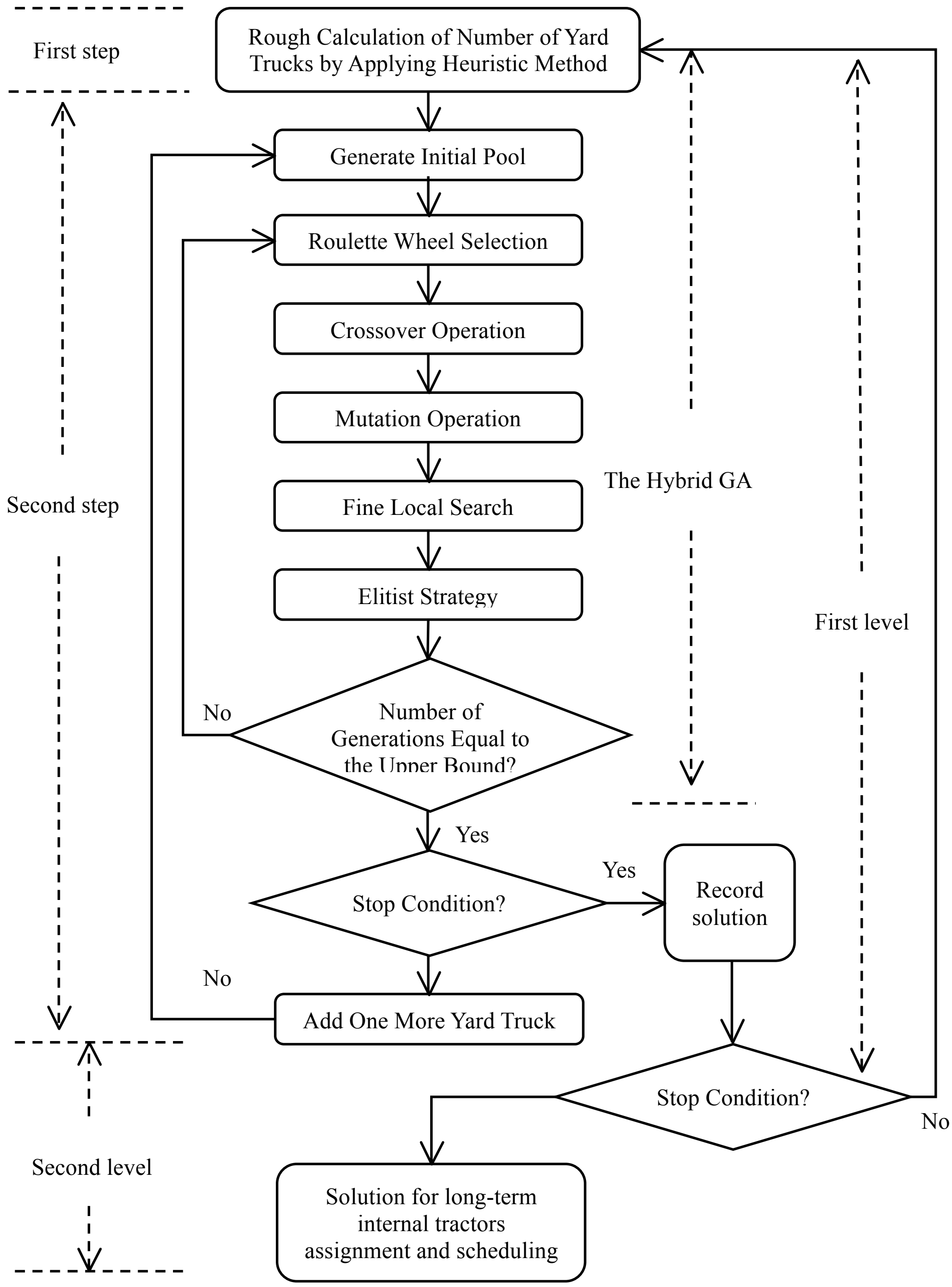

Figure 5.2 Workflow of the proposed heuristic

5.4.1 Hybrid Genetic Optimization Algorithm

The proposed hybrid GA is composed of two steps. In the first step, the number of internal trucks is roughly calculated by applying the nearest distance heuristic method. The principle of the nearest distance heuristic method is to choose the nearest storage location and the nearest successive containers for storage and routing. In the second step, the iterations will cease when the hybrid GA reaches the stopping condition, giving the best solution for internal truck scheduling and storage allocation, as shown in Figure 5.2.

5.4.1.1 Chromosome Encoding

Two different types of genes are applied to represent the containers and yard trucks. A positive integer gene represents a container, and the gene is composed of five parameters, representing index, time window a_i, time window b_i, origin location, and destination location of the container, as shown in Figure 5.3. The sequence of positive genes is performed from left to right. A negative integer gene represents an internal truck and contains information on the index of the internal truck. An internal truck will handle containers that are between two successive negative genes, as shown in Figure 5.4. The first yard truck would sequentially process containers 4, 8, 2 and 5; the second truck would process containers 9, 1, 10, 3, 7 and 6.

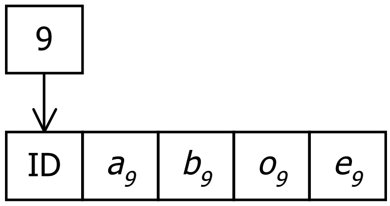

Figure 5.3 Example of gene representation

4	8	2	5	-1	9	1	10	3	7	6	-2

Figure 5.4 Example of chromosome encoding

5.4.1.2 Crossover Operation

In the proposed approach, the sequence of genes represents the critical structure of the chromosomes. During evolution, a pair of parents will generate a pair of offspring. The offspring with better fitness will replace the original parents in the mating pool. A pair of offspring can be generated by following the steps below.

Generating offspring 1 (O_1)

Step 1: Put all the genes of both parent P_1 and parent P_2 handled by the first truck into a new gene set Λ and remove the duplicated genes.

Step2: Let Θ be the sequencing the genes in Λ according to the non-decreasing order of their earliest possible time.

Step 3: Add the genes in the corresponding truck in O_1 according to their order in set Θ and remove these genes from set Λ.

Step 4: Add all the genes in the next truck for both parent P_1 and parent P_2 into set Λ. Then, delete the duplicated genes and the genes that have been inserted in O_1.

Step 5: Repeat steps 2 – 4 until all the trucks are assigned.

Generating offspring 2 (O_2)

The procedure of generating O_2 is similar to generating O_1. In step two, set Θ is a set of sequencing genes in Λ according to the non-decreasing order of their due time.

5.4.1.3 Mutation Operation

The objective of a mutation operator is to maintain the chromosome diversity and improve the ability of local searching. Each chromosome contains information on container sequence, number of container handling by an internal truck, and the storage location for each container. During the mutation operation, three different mutation methods are applied, according to three types of information.

In the first mutation method for changing the storage location, an import container is selected and its storage location is replaced with another one randomly obtained from storage locations in which the container's travel time is within the container's due time. In the second mutation method for changing the two containers' positions, a container is randomly swapped with another container. In the third mutation approach for changing the number of containers in two trucks, a container is taken from one truck and put on another truck.

5.4.1.4 Genetic Evolution

In the proposed approach, the evolution mechanism is shown in the first level of Figure 5.2. At the beginning, the initial pool is generated by heuristic rules and random generation. Two of the chromosomes are generated according to the earliest possible time combined with the nearest storage location, and the earliest due time combined with the nearest storage location. The rest of the chromosomes are randomly generated. The roulette wheel selection approach is applied for forming the mating pool. Furthermore, to keep the best chromosome(s), an elitist strategy is used, which stores the best chromosome to replace the worst chromosome. It is common to use the fitness value to demonstrate the quality of a chromosome. The objective is to minimize the weighted summation of the total internal truck deployment cost and the total delay cost. Thus, the fitness value of a chromosome can be the reciprocal of its objective function value Δ, as shown in Eq. (5.25).

$$\text{Fitness} = 1 / \Delta \tag{5.25}$$

A local searching method proposed by Chung *et al*. (2011) is applied in this study to make the GA converge faster and steadier. In one part of a chromosome, a set of continuous genes is selected as a segment. All combinations of genes within this segment are tested and the best one is recorded.

5.4.2 Linear Programming Methodology

The strategy of deploying internal trucks is determined by linear programming. Based on the calculation given in the previous sub-section, the number of internal trucks deployed each day T_r can be obtained. Hence, the number of owned and rented internal trucks can be calculated using the following formulations.

Objective function:

Minimize: $$Z = \alpha_1 H + \alpha_2 \sum_{r \in R} H_r + \alpha_3 \sum_{r \in R} S_r \tag{5.26}$$

Subject to:

$$H \geq H_r \qquad \forall \ r \in R \tag{5.27}$$

$$H_r + S_r = T_r \qquad \forall \ r \in R \tag{5.28}$$

$T_r \geq H_r \qquad \forall \ r \in R \qquad (5.29)$

$T_r \geq S_r \qquad \forall \ r \in R \qquad (5.30)$

Constraints (5.27) calculate the number of owned yard trucks. Constraints (5.28) ensure that the total number of the two types of trucks is equal to the result obtained in step one. Constraints (5.29) and (5.30) are domain constraints of the decision variables.

5.5 Numerical Experiments

In this section, computational experiments are used to analyze the performance of the proposed heuristic algorithm. The proposed algorithm is coded using Java Language and executed on a PC with Intel Core i7 3.4 GHz and 8 GB RAM. In the computational experiments, the container throughput of Hong Kong is obtained from the website of the Hong Kong Government using data from the year 2012. The average number of containers handled by a terminal is around 5000 per day. An example of the amount of loading, unloading containers and available storage locations is shown in Appendix 2. The locations of the export containers' origin and destination, and import containers' origin and storage space are created following a uniform distribution in a two-dimension square space from $0*0m^2$ to $1500*1500m^2$. The number of storage locations is always larger than the number of import containers. Both the loading process and unloading process take 2 minutes and the truck speed is 3 m/s (11km/h). Moreover, it is assumed that a truck works 24 hours a day. The beginning of a time window is generated from (0, 72000) (unit: seconds) uniformly and the due time is generated from (1000, 1500) (unit: seconds).

5.5.1 Sensitivity Analysis

To analyze how the cost of owning a truck, using an owned truck and renting a truck affect the objective function, a number of numerical experiments is performed. The cost data are obtained from an operation manager in one of the container companies in Hong Kong (because of confidentiality, the company's name is not given). In order to demonstrate the relationship among the three parameters (cost of owning a truck, using an owned truck, and outsourcing), the parameters' value needs to be changed methodically. Thus, it is also assumed that the cost of owning a truck, using an owned truck, and renting a truck are increased by US$10000, US$25, and US$100 respectively. Three series of experiments are designed by fixing one cost parameter and changing the other two cost parameters, with average computational time for each day's schedule around 87 seconds. To solve the integrated problem by using the proposed hybrid GA, the parameters are set as follows: population size 10, crossover rate P_C, 0.8, mutation rate P_M, 0.9, and number of generations 1000.

Figure 5.5 shows the relationship among the number of owned internal trucks, cost of renting a truck, and the cost of owning a truck when the cost of using an owned truck is fixed at US$25 per day. Figure 5.6 shows the relationship among the number of owned internal trucks, cost of using an owned truck, and cost of owning a truck when the cost of renting a truck is fixed at US$300 per day. Figure 5.7 shows the relationship among the number of owned internal trucks, the cost of using an owned truck and cost of renting a truck when cost of owning a truck is fixed at US$30000.

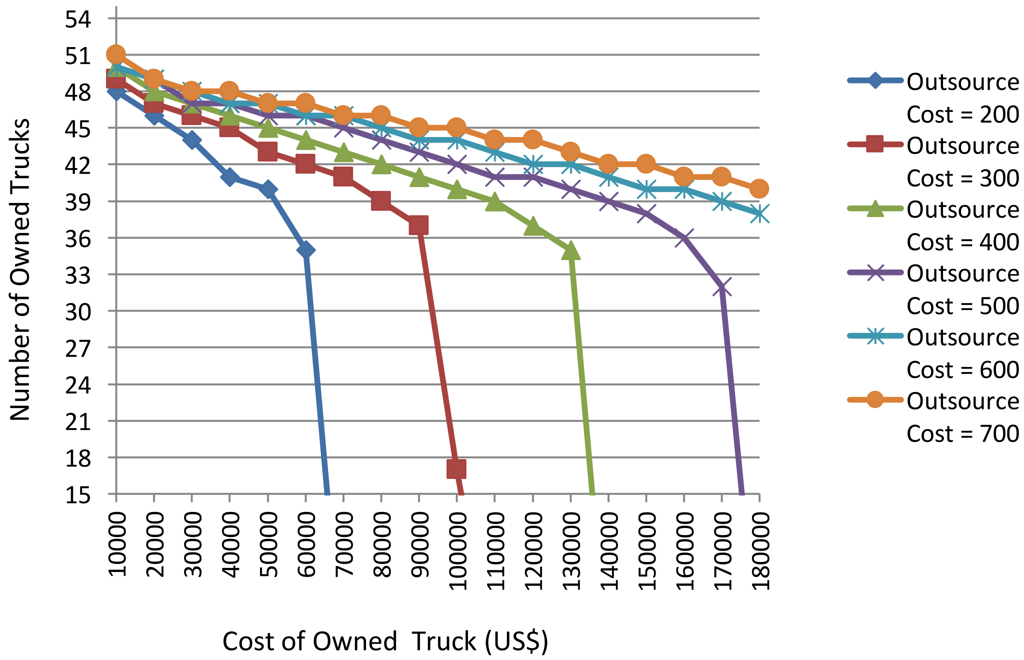

Figure 5.5 Effect of renting cost and owned truck cost on the number of owned trucks

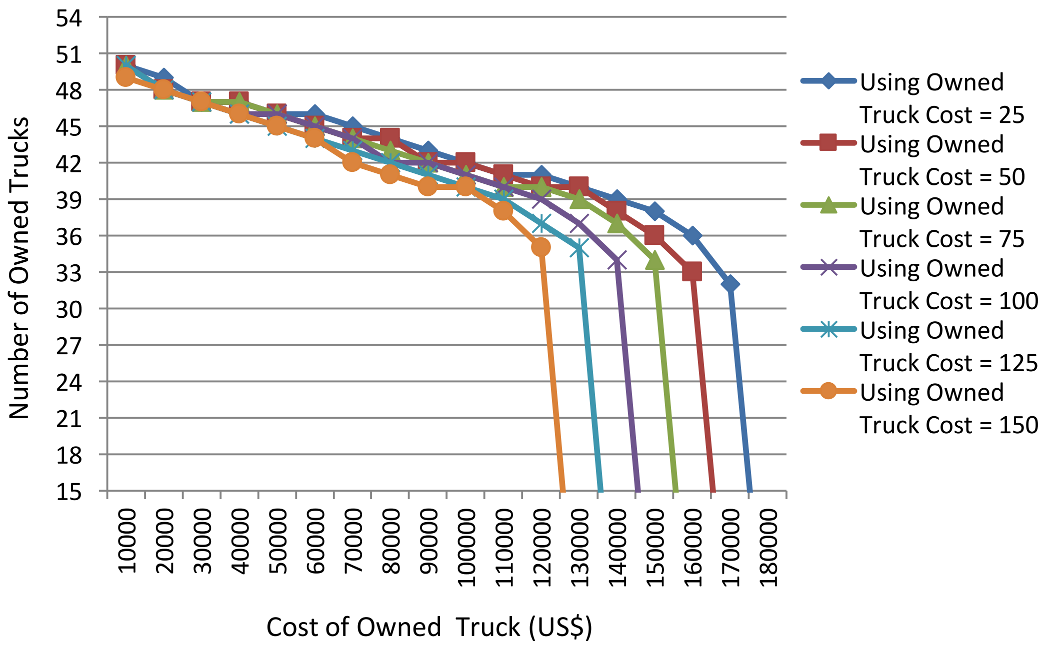

Figure 5.6 Effect of using owned truck cost and the owned truck cost on the number of owned trucks

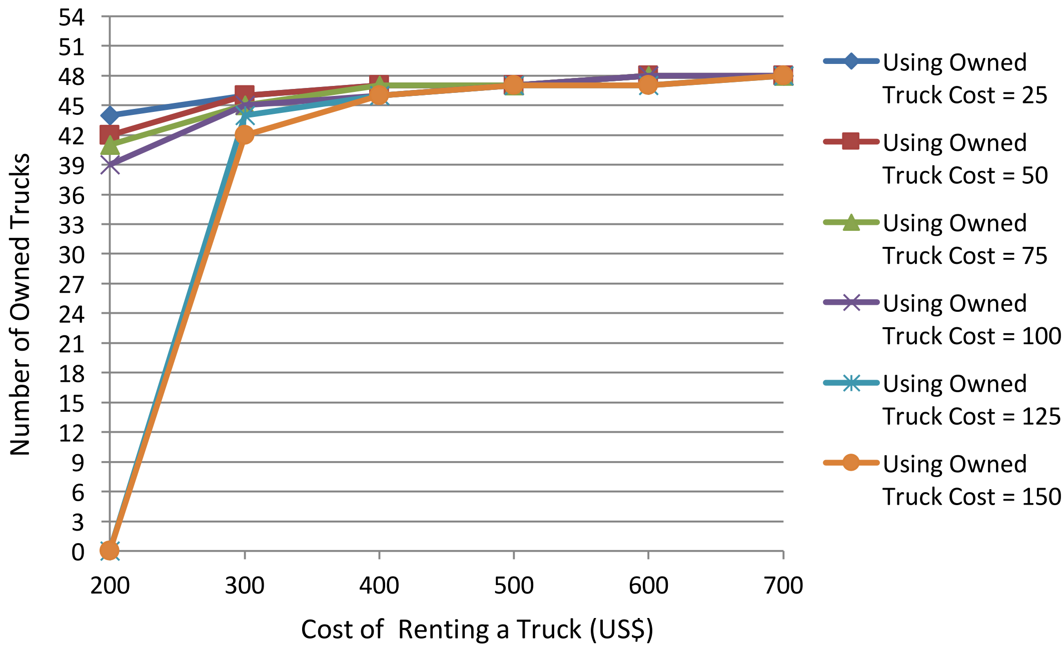

Figure 5.7 Effect of using owned truck cost and renting cost on the number of owned trucks

Figures 5.5 - 5.7 evaluate the effect of the three cost parameters. Comparing the results from Figures 5.5 and 5.6 it can be seen that the renting cost has a greater influence than the cost of using the owned truck on the number of owned trucks. Comparing the results from Figures 5.5 - 5.7 it can be seen that the cost of owning a truck has a greater influence on the number of owned trucks than other parameters.

5.5.2 Analysis of Number of Internal Trucks

In this section, computational experiments are used to analyze the performance of the proposed heuristic algorithm. The commercial software IlogCplex version 12.4 is used for calculation of the linear programming. The minimum number of trucks needed each day is first calculated, as shown in Figure 5.8.

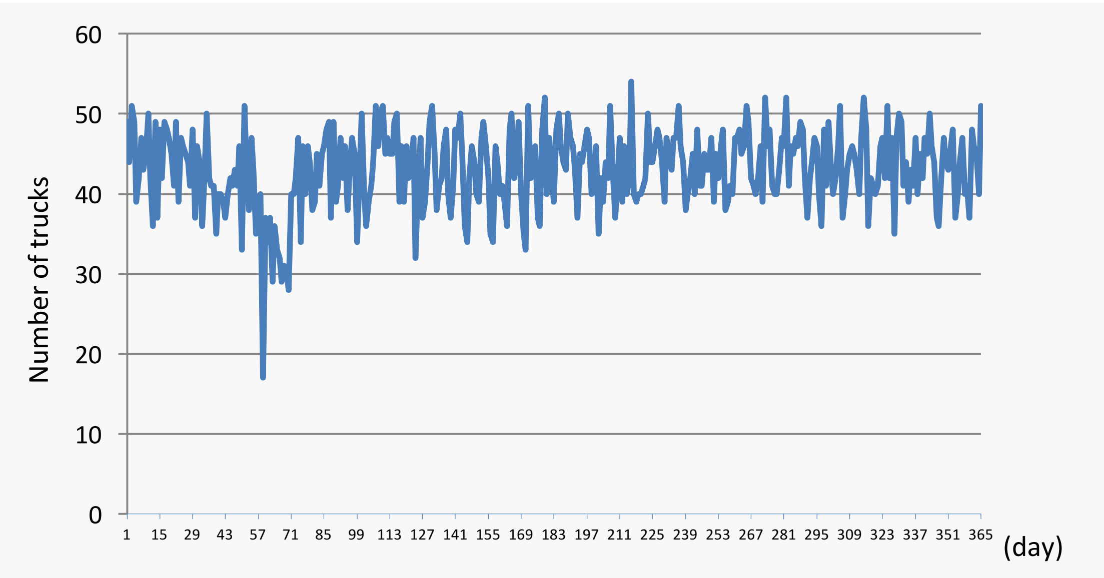

Figure 5.8 Number of trucks deployed each day

The optimal strategy of deploying yard trucks can be calculated as soon as the number of trucks for each day is obtained. Three parameters are fixed in order to analyze the performance of the optimal strategy calculated by the proposed heuristic algorithm. The cost of owning and renting trucks is defined as: α_1 is equal to US$150000, α_2 is equal to US$50 and α_3 is US$500. Then, the number of owned trucks is calculated as 45. In addition, another three strategies for deploying trucks are proposed for comparison. In the second strategy, the number of owned trucks equals the annual average number of trucks. For the third strategy, all the trucks are rented. Sufficient trucks are brought in to cover all the containers in the fourth strategy. Figure 5.9 shows the cost of the four strategies. Using the deployment strategy obtained from the proposed approach significantly reduces the cost of deploying yard trucks. Since the strategy of deploying yard trucks determines terminal economic benefits, the integration of internal vehicle scheduling and storage space assignment can improve the efficiency of container terminal operations. The proposed integrated approach is able to provide a good truck deployment strategy and storage allocation method.

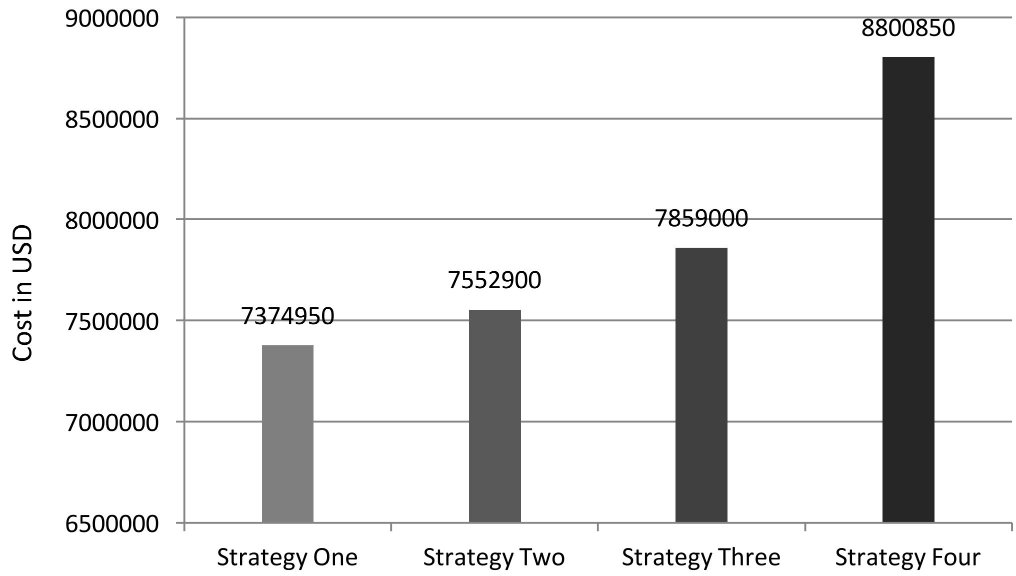

Figure 5.9 Cost of depolying trucks for different strategies

5.6 Summary

Internal truck deployment strategies and scheduling with container storage location planning are important issues in a container terminal, but have not been studied holistically. In this research, the integrated problem is solved by the proposed heuristic approach consisting of two levels. The first level can be further divided into two steps. In the first step, the number of yard trucks depolyed each day is roughly calculated as an input for the second step in order to speed up the calculation. In the second step, a hybrid genetic algorithm with exhaustive heuristic and guidance mutation deals with the integrated problem of yard truck scheduling and storage allocation. The crossover operation of the proposed genetic algorithm is based on information concerning a container's ready time and due time. The mutation operator combines a three-way mutation approach. Three series of sensitivity analysis experiments are conducted to investigate the influence of different parameters on the objective terms. Experimental results show that container terminals are more sensitive to the cost of owning an internal truck than other costs. After finding the number of trucks needed each day, with no delays, obtained in the first level, the strategy of deploying yard trucks, for example owned or rented, can be obtained by linear programming. The computational experiments show that the proposed method minimizes the cost of employing rented and owned yard trucks.

Chapter 6 Mathematical Model for Storage of Transhipment Containers

6.1 Introduction

Container terminals can be divided into gateway ports and transhipment hubs. The major operation of a gateway port is importing and exporting containers. Nevertheless, the major activity of a transhipment hub is transshipping containers from one vessel to another. In the last two chapters, the operation issues occurring in gateway ports are investigated. The major concerns described in this chapter and the following chapter is the transhipment operation problems occurring in transhipment hubs.

The focus is on the determination of transhipment container storage locations in the storage yard. Before a vessel arrives at a terminal, the terminal operator assigns the vessel to a berth. As soon as the vessel has moored, a number of transhipment containers are unloaded for the vessel, following a working plan. The quay cranes unload transhipment containers from the arriving vessel onto transport vehicles. Then, the transport vehicles deliver the transhipment containers from quayside to yard side for temporary storage. The difference between container storage in gateway ports and transhipment hubs is that a transhipment container will be stored in yard side until it is loaded onto a departing vessel. Thus, the storage assignment of transhipment containers should be related to both the unloading distance from the arriving vessel to the storage yard, and the loading distance from the storage yard to the departing vessel. The technical details for the problem are illustrated in the corresponding sections. The remainder of this chapter is organized as follows: in section 6.2 a detailed description is given; a mathematical model is formulated in section 6.3; in section 6.4 the experimental instances and computational results are presented to verify the proposed mathematical model; and conclusions are given in the last section.

6.2 Problem Description

When vessel i arrives at a berth, transhipment containers will be unloaded from vessel i to some pre-reserved sub-block k. The transhipment containers are stored in the yard by utilizing the consignment strategy. By using the consignment strategy, the transhipment containers with same departing vessel will be assigned to same storage locations (Zhen *et al.*, 2011a). Specifically, the transhipment containers delivered from vessel i to vessel j and assigned to the same storage locations have the same loading and unloading routing according to the passing line of yard trucks, as shown in Figure 6.1. Then group z is used to gather the containers with the same arriving vessel, departing vessel, and storage locations, with the aim of simplifying the storage space assignment for transhipment containers. The berthing position of vessel i is assumed to be pre-defined as berth segment b. The problem is to assign proper storage locations for transhipment containers with the objective of minimizing the total transhipment distance. Details of the corresponding mathematical model are presented in the following section.

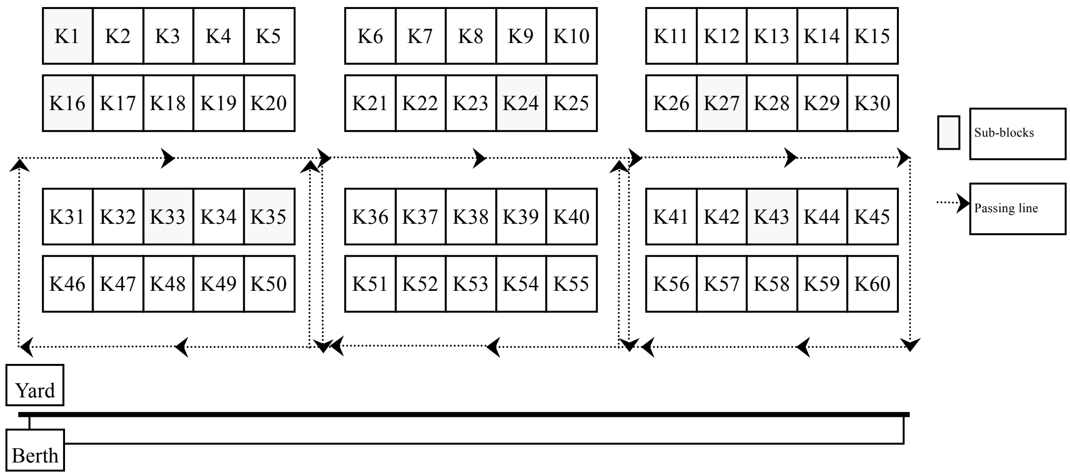

Figure 6.1 Passing line of yard trucks in a container terminal

6.3 Mathematical Formulation

Notations

Index:

i, j: Index of vessels.

k: Index of sub-blocks.

z: Index of container groups.

b: Index of berth segments.

Input data:

V: Set of vessels.

B: Set of berth segments.

K: Set of sub-blocks.

GP: Set of groups.

BV: Maximum number of containers that a sub-block can store.

GN: Number of containers in a group.

$\mu_{z,i,j}$: $\mu_{z,i,j} = 1$, denotes group z is located in vessel i and waiting for the transhipment from vessel i to vessel j; $\mu_{z,i,j} = 0$, otherwise; $i, j \in V$, $i \neq j$.

$D^U_{k,b}$: Length of unloading path between each pair of berth segment b and sub-block k; $k \in K$, $b \in B$.

$D^L_{k,b}$: Length of loading path between each pair of sub-block k and segment b; $k \in K$, $b \in B$.

$\varphi_{i,k}$: $\varphi_{i,k} = 1$, denotes vessel i has a reservation sub-block k; $\varphi_{i,k} = 0$, otherwise; $i \in V$, $k \in K$.

$\omega_{i,b}$: $\omega_{i,b} = 1$, denotes vessel i is berthed in berth segment b; $\omega_{i,b} = 0$, otherwise; $i \in V$, $b \in B$.

$\psi^S_{z,b} \in \{0,1\}$: set to one if the starting position of group z is berthed in berth segment b, and zero otherwise; $z \in GP$, $b \in B$.

$\psi^E_{z,b} \in \{0,1\}$: set to one if the ending position of group z is berthed in berth segment b, and zero otherwise; $z \in GP$, $b \in B$.

M: a large positive number.

Note that $\psi^S_{z,b}$ and $\psi^E_{z,b}$ are decided by $\omega_{i,b}$ and $\mu_{z,i,j}$ since a group of containers is transported by the arriving vessel and departing vessel. Thus, $\psi^S_{z,b}$ and $\psi^E_{z,b}$ can be calculated as follows:

$$\psi^S_{z,b} = \sum_{i \in V, j \in V, i \neq j} \mu_{z,i,j} \cdot \omega_{i,b} \; \forall b \in B, \qquad \forall z \in GP \tag{6.1}$$

$$\psi^E_{z,b} = \sum_{i \in V, j \in V, i \neq j} \mu_{z,i,j} \cdot \omega_{j,b} \; \forall b \in B, \qquad \forall z \in GP \tag{6.2}$$

Decision variables:

$x_{z,k} \in \{0,1\}$: set to one if group z is allocated to sub-block k, and zero otherwise; $z \in GP$, $k \in K$;

$\lambda_z \geq 0$: the processing distance of group z; $z \in GP$

The problem model is formulated as follows:

$$[\mathrm{P^L}]: \text{Minimize: } Z^{Tru} = GN \cdot \sum_{z \in GP} \lambda_z \tag{6.3}$$

Subject to:

$$\sum_{k \in K} x_{z,k} = 1 \qquad \forall z \in GP \qquad (6.4)$$

$$\mu_{z,i,j} \cdot x_{z,k} \leq \varphi_{j,k} \ \forall i, j \in V, \ i \neq j, \qquad \forall k \in K, \ \forall z \in GP \qquad (6.5)$$

$$\sum_{i \in V, i \neq j} \sum_{z \in GP} GN \cdot \mu_{z,i,j} \cdot x_{z,k} - M \cdot (1 - \varphi_{j,k}) \leq BV \qquad \forall j \in V, \ \forall k \in K$$

$$(6.6)$$

$$\lambda_z = \sum_{b \in B} \sum_{k \in K} \psi^S_{z,b} \cdot x_{z,k} \cdot D^U_{k,b} + \sum_{b \in B} \sum_{k \in K} \psi^E_{z,b} \cdot x_{z,k} \cdot D^L_{k,b} \qquad \forall z \in GP \qquad (6.7)$$

$$x_{z,k} \in \{0,1\} \qquad \forall z \in GP, \forall k \in K \qquad (6.8)$$

$$\lambda_z \geq 0 \qquad \forall z \in GP \qquad (6.9)$$

Objective (6.3) is to minimize the distance of transhipment of the transhipment containers. Constraints (6.4) guarantee that each group of containers can only be allocated to one sub-block. Constraints (6.5) ensure that if container group z is transshipped from vessel i to vessel j, group z can only be allocated a sub-block that is reserved for vessel j. Constraints (6.6) ensure that the total load of each sub-block must not exceed its capacity. Constraints (6.7) calculate the transhipment distance of each group. Constraints (6.8) and (6.9) define the variables.

6.4 Computational Example

A computational example is presented to illustrate the problem of assigning transhipment containers in the yard side, and to verify the accuracy of the proposed mathematical model. The mathematical models presented in the proposed algorithm are implemented by CPLEX 12.4 (NetBeans IDE 7.4, Java 8) on a PC (Intel Core i7-2600, 3.4 GHz; Memory, 8 GB).

The horizontal passing line is unidirectional and the vertical passing line is bidirectional as shown in Figure 6.1. Thus, the shortest path between a berthing position and a sub-block is unique. Sample data is presented in Table 6.1 and some of the binary input data are shown in Table 6.2.

Table 6.1 Sample data

Number of vessels	Quay length (m)	Number of yard trucks	Number transhipment containers
20	700	25	8520
Maximum containers of a sub-block	Number of containers in a group	Number of sub-blocks	Number of berth segments
240	60	120	10

Table 6.2 Partial binary input data

$\mu_{1,1,1}$	0	$\omega_{1,1}$	0	$\varphi_{1,1}$	0
$\mu_{1,1,2}$	0	$\omega_{1,2}$	0	$\varphi_{1,2}$	0
$\mu_{1,1,3}$	0	$\omega_{1,3}$	0	$\varphi_{1,3}$	1
$\mu_{1,1,4}$	0	$\omega_{1,4}$	0	$\varphi_{1,4}$	0
$\mu_{1,1,5}$	0	$\omega_{1,5}$	0	$\varphi_{1,5}$	0
$\mu_{1,1,6}$	1	$\omega_{1,6}$	0	$\varphi_{1,6}$	0
$\mu_{1,1,7}$	0	$\omega_{1,7}$	0	$\varphi_{1,7}$	0
$\mu_{1,1,8}$	0	$\omega_{1,8}$	1	$\varphi_{1,8}$	0
$\mu_{1,1,9}$	0	$\omega_{1,9}$	0	$\varphi_{1,9}$	0
$\mu_{1,1,10}$	0	$\omega_{1,10}$	0	$\varphi_{1,10}$	0
$\mu_{1,1,11}$	0	$\omega_{2,1}$	0	$\varphi_{1,11}$	0
$\mu_{1,1,12}$	0	$\omega_{2,2}$	0	$\varphi_{1,12}$	0
$\mu_{1,1,13}$	0	$\omega_{2,3}$	0	$\varphi_{1,14}$	0
$\mu_{1,1,14}$	0	$\omega_{2,4}$	0	$\varphi_{1,15}$	0
$\mu_{1,1,15}$	0	$\omega_{2,5}$	0	$\varphi_{1,16}$	0
$\mu_{1,1,16}$	0	$\omega_{2,6}$	0	$\varphi_{1,17}$	0

The computational time of this example is 83 seconds, after which the computer programs can obtain the calculation results of the decision variables, partially shown in Table 6.3, with 3244800 as the objective of this example.

Table 6.3 Partial results of decision variables

$x_{z,k}$				λ_z			
$x_{1,1}$	0	$x_{2,1}$	0	λ_1	400	λ_{16}	300
$x_{1,2}$	0	$x_{2,2}$	0	λ_2	400	λ_{17}	300
$x_{1,3}$	0	$x_{2,3}$	0	λ_3	400	λ_{18}	300
$x_{1,4}$	0	$x_{2,4}$	0	λ_4	400	λ_{19}	500
$x_{1,5}$	0	$x_{2,5}$	0	λ_5	620	λ_{20}	500
$x_{1,6}$	0	$x_{2,6}$	0	λ_6	620	λ_{21}	370
$x_{1,7}$	1	$x_{2,7}$	1	λ_7	485	λ_{22}	500
$x_{1,8}$	0	$x_{2,8}$	0	λ_8	485	λ_{23}	370
$x_{1,9}$	0	$x_{2,9}$	0	λ_9	485	λ_{24}	500
$x_{1,10}$	0	$x_{2,10}$	0	λ_{10}	485	λ_{25}	370
$x_{1,11}$	0	$x_{2,11}$	0	λ_{11}	100	λ_{26}	370
$x_{1,12}$	0	$x_{2,12}$	0	λ_{12}	100	λ_{27}	200
$x_{1,13}$	0	$x_{2,13}$	0	λ_{13}	100	λ_{28}	200
$x_{1,14}$	0	$x_{2,14}$	0	λ_{14}	100	λ_{29}	530
$x_{1,15}$	0	$x_{2,15}$	0	λ_{15}	300	λ_{30}	200

6.5 Summary

In this chapter, the assigning of proper storage locations for transhipment containers is presented and modeled considering the practical constraints. As some of the transhipment containers are unloaded from the same arriving vessel, stored in the same sub-blocks and are loaded onto the same departing vessel, these transhipment containers can be identified as a group. Based on the group concept, a mathematical model is presented, and solved by using the software package CPLEX.

In the next chapter, the impact of transhipment group size on the objective is analyzed. Furthermore, since the delivery of the transhipment containers is also related to the yard trucks, the transhipment operation is studied with consideration of the scheduling yard trucks to perform a number of transhipment jobs. Since the seaside operation is connected to the yard-side operation, as described in the previous chapters, the following chapter studies the transhipment operation considering yard truck scheduling combined with the seaside operation.

Chapter 7 Integration Problem of Storage Space Assignment, Yard Truck Scheduling in Transhipment Hubs

7.1 Introduction

This chapter focuses on the transhipment activity in transhipment hubs. The transhipment of containers is a major activity for large container terminals, such as the Ports of Singapore, Hong Kong, etc. The number of containers being transshipped is increasing faster than the container port throughput (Fransoo and Lee, 2013; Zhen, 2014a). Efficient transhipment operations minimize the turnaround time of vessels, and produce a significant improvement in container throughput.

The productivity of container terminals can be measured by two factors, i.e. ship operations and delivery operations (Kim and Park, 2004). Ship operations relate to the operations of containers unloading from or loading onto a ship, while delivery operations relate to containers transferred to and from yard trucks (Kim and Park, 2004). Both operations have been well studied by researchers. However, recently, it was found that the bottleneck of terminal operations is primarily caused by yard side operations, rather than quayside operations, because of the development of quayside equipment and technologies (Chang *et al*., 2011; He *et al*., 2010; Zhen, 2014b). Both storage location assignment and yard truck routing are important in improving the efficiency of container transhipment. This study therefore investigated the yard operations, which concern transhipment containers storage allocation, and the routing of yard trucks.

Since the operations in the yard side and quayside are related, the aim is to develop a new model to deal with the integration problem in the yard side that can be connected to the quayside. The developed model is more comprehensive and practical than those in the existing literature. Particularly, the proposed model is an integration of storage allocation and yard truck scheduling in transhipment hubs. The remainder of this chapter is organized as follows: in section 7.2 a detailed problem description is given; a mathematical model is formulated in section 7.3; in section 7.4 a heuristic algorithm is proposed; the experimental instances and computational results are described in section 7.5; and conclusions are provided in the last section.

7.2 Problem Description and Mathematical Formulation

The approach is an extension of that given by Zhen *et al*. (2011a), where operations in both the quayside and yard side are considered. In the quayside, the berth location assignment is decided by considering the quay crane working profile, vessel arriving and departing schedule, and berth length limitation. In the yard side, in order to minimize the route distance of the transhipment, the number of blocks reserved for a vessel is calculated with consideration of traffic congestion in the neighboring blocks. However, the route distance of the transhipment is associated with the traveling route and empty trips of the yard trucks. Moreover, the storage location assignment decision cannot be obtained from the block reservation plan. To enrich the idea of solving berth template planning and yard template planning by integration, the yard template planning is further extended by considering: (i) the exact temporary storage location that is allocated to a transhipment container, and (ii) the travel distance (including both processing distance and empty trip distance) in the objective. The decision problems in the quayside, i.e. berth assignment and quay crane assignment, have been comprehensively discussed in the model of Zhen *et al.* (2011a), which can be linked with this proposed model by using the variables, discussed below.

Consignment strategy is commonly applied in transhipment hubs, such as the port of Hong Kong and Singapore. The transhipment and export containers with the same departing vessel are allocated to the same reversed sub-blocks by using this strategy. As transhipment containers are transshipped from one vessel i to another vessel j, the number of sub-blocks reserved for vessel j is known in advance. It is also assumed that $\varphi_{j,k}$, which is a decision variable indicating that the sub-block is reserved for vessel j, is given. This assumption helps to link the new model with Zhen *et al.*'s (2011a) model by using the notation.

As shown in Figure 7.1, sub-blocks K1, K16 and K27 are reserved for Vessel *A*. The containers, which need to be transshipped from some vessels, i.e., Vessel *B*, Vessel *C* and Vessel *D*, to Vessel *A*, are allocated to these sub-blocks. As the travel distance from each sub-block to each vessel is different, the terminal managers should decide which container is allocated to which reserved sub-block. This container storage location allocation decision will obviously influence both the loading and unloading travel distance of each container. An inappropriate decision forces a yard truck to travel a longer distance for processing both loading and unloading operations, e.g., a yard truck needs to travel a longer distance if the transhipment containers, which are transshipped from Vessel *C* to Vessel *D*, are allocated to sub-blocks K33 and K35 rather than allocated to sub-block K43. However, a number of transhipment containers, which may be unloaded from one vessel, stored in a sub-block and loaded onto another vessel, have the same transporting distance since they have the same transporting starting location, temporary storage location and transporting ending spot. Thus, a certain number of transhipment containers that are unloaded from the same vessel and loaded onto another same vessel, is classified as a group z. It is also assumed that the containers in one group have the same storage location.

This grouping can help simplify the calculation in which the group volume is changeable. When the number of transhipment containers is large, a large group volume can speed up the calculation, and vice versa. Specifically, when the group volume is equal to one, a group becomes a container and the storage location for every single container will be calculated. On the other hand, when the group volume is equal to the sub-block volume, the decision on storage allocation, i.e. the selection from reserved sub-blocks, is the same as in Zhen *et al*. (2011a).

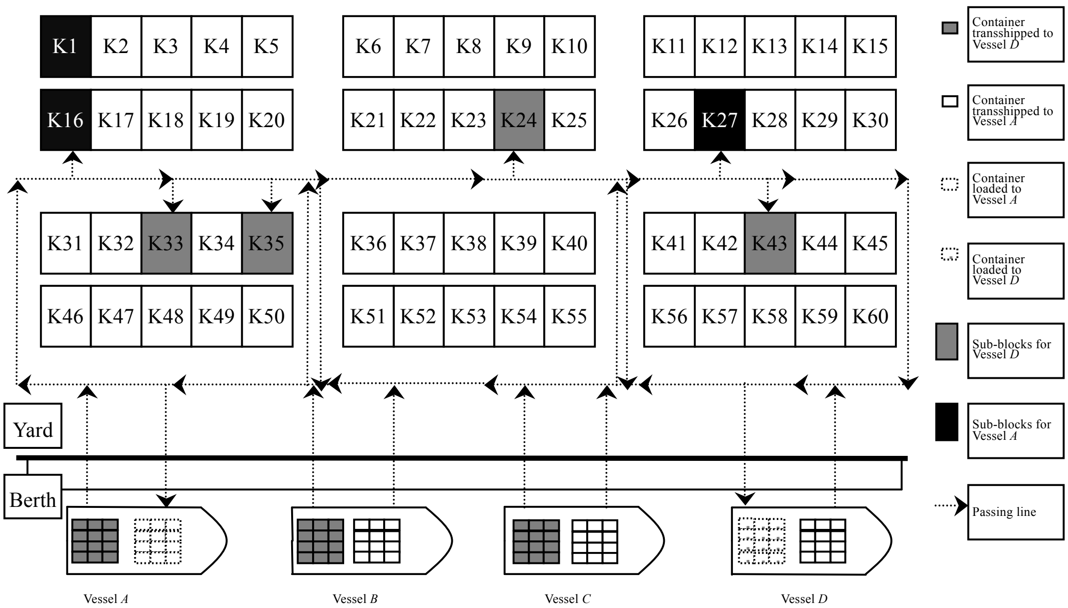

Figure 7.1 Typical container terminal layout

To tranship container group z from vessel i to vessel j, group z needs to be unloaded from vessel i, stored in a sub-block for a while and then loaded to vessel j. The loading or unloading process of group z is defined as a loading job or an unloading job, denoted as *ca* and *cb* respectively. Since the origin location of a loading job and the destination location of an unloading job are unknown, an empty trip between two jobs is formed under four conditions, as shown in Figures 7.2a to 7.2d. Thus the determination of the processing distance and the empty travel distance should be considered for four conditions. Figure 7.2a shows a yard truck successively taking a loading job and another loading job. Figure 7.2b shows a yard truck successively taking a loading job and an unloading job. Figure 7.2c shows a yard truck successively taking an unloading job and a loading job. Figure 7.2d shows a yard truck successively taking an unloading job and another unloading job.

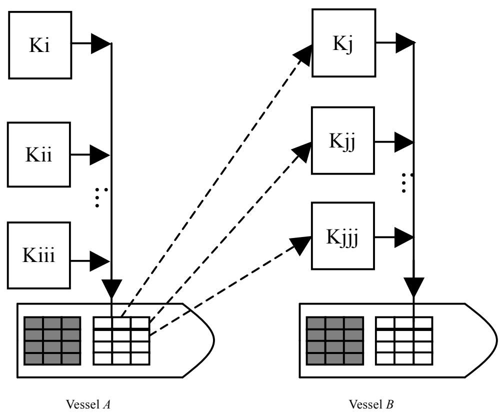

Figure 7.2a loading + loading

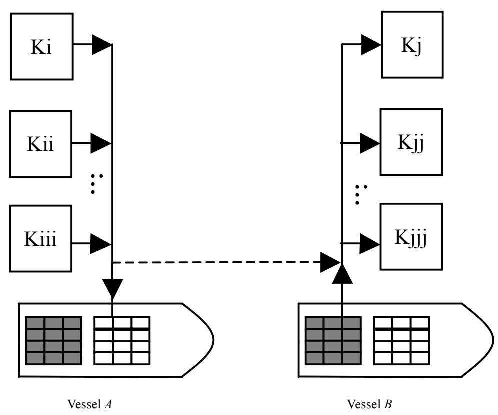

Figure 7.2b loading + unloading

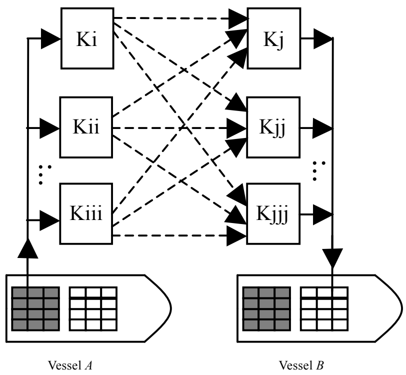

Figure 7.2c unloading + loading

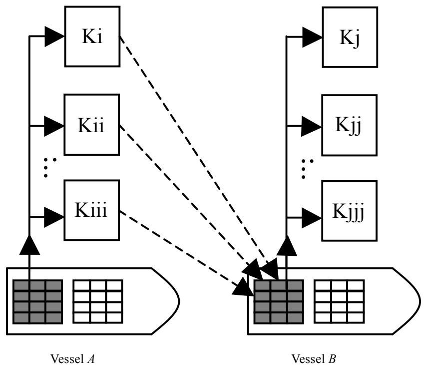

Figure 7.2d unloading + unloading

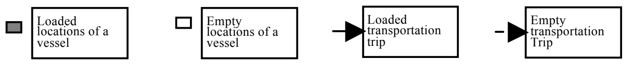

Figure 7.2 Container transhipment procedures

7.3 Mathematical Formulation

7.3.1 The Mathematical Model

The mathematical formulation for the transhipment operations in the yard side is given as follows:

Notations:

Index:

i, j: Index of vessels.

k: Index of sub-blocks.

z: Index of container groups.

ca, cb: Index of jobs.

b: Index of berth segments.

Input data:

V: Set of vessels.

B: Set of berth segments.

K: Set of sub-blocks.

GP: Set of groups.

BV: Maximum number of containers that a sub block can store.

GN: Number of containers in a group.

$\mu_{z,i,j}$: $\mu_{z,i,j}$ = 1, denotes group *z* is located in vessel *i* and waiting for the transhipment from vessel *i* to vessel *j*; $\mu_{z,i,j}$= 0, otherwise; $i, j \in V$, $i \neq j$.

TN: Number of trucks.

ds: A dummy start job.

de: A dummy end job.

JA: Set of loading jobs.

JB: Set of unloading jobs.

JJ: Set of loading and unloading jobs; $JJ = JA \cap JB$.

JS: Set of loading, unloading jobs and the dummy start job; $JC = JJ \cap \{ds\}$.

JE: Set of loading, unloading jobs and the dummy end job; $JC = JJ \cap \{de\}$.

$ld_{z,ca}$: $ld_{z,ca}$= 1, denotes job *ca* is the loading job of group z; $ld_{z,ca}$= 0, otherwise; $z \in GP$, $ca \in JJ$.

$ud_{z,cb}$: $ud_{z,cb}$= 1, denotes job *cb* is the unloading job of group z; $ud_{z,cb}$= 0, otherwise; $z \in GP$, $ca \in JJ$.

$D^{B}_{b,b'}$: Length of traveling path between each pair of berth segment b and berth segment b'; b, $b' \in B$.

$D^{K}_{k,k'}$: Length of traveling path between each pair of sub-block k and sub-block k'; k, $k' \in K$.

$D^{U}_{k,b}$: Length of unloading path between each pair of berth segment b and sub-block k; $k \in K$, $b \in B$.

$D^{L}_{k,b}$: Length of loading path between each pair of sub-block k and segment b; $k \in K$, $b \in B$.

$\varphi_{i,k}$: $\varphi_{i,k}$ = 1, denotes vessel i has a reservation sub-block k; $\varphi_{i,k}$ = 0, otherwise; $i \in V$, $k \in K$.

$\omega_{i,b}$: $\omega_{i,b}$ = 1, denotes vessel i is berthed in berth segment b; $\omega_{i,b}$ = 0, otherwise; $i \in V$, $b \in B$.

$\psi^{S}_{z,b} \in \{0,1\}$: set to one if the starting position of group z is berthed in berth segment b, and zero otherwise; $z \in GP$, $b \in B$.

$$\psi^{S}_{z,b} = \sum_{i \in V, j \in V, i \neq j} \mu_{z,i,j} \cdot \omega_{i,b} \quad \forall b \in B, \quad \forall z \in GP \tag{7.1}$$

$\psi^{E}_{z,b} \in \{0,1\}$: set to one if the ending position of group z is berthed in berth segment b, and zero otherwise; $z \in GP$, $b \in B$.

$$\psi^{E}_{z,b} = \sum_{i \in V, j \in V, i \neq j} \mu_{z,i,j} \cdot \omega_{j,b} \quad \forall b \in B, \quad \forall z \in GP \tag{7.2}$$

spe: Yard truck speed.

M: A large positive number.

Decision variables:

$x_{z,k} \in \{0,1\}$: Set to one if group *z* is allocated to sub-block *k*, and zero otherwise; $z \in GP$, $k \in K$.

$y_{ca,cb} \in \{0,1\}$: Set to one if job *ca* and *cb* are successive jobs and handled by the same truck, and zero otherwise; $ca \in JS$, $cb \in JE$.

$\tau_{ca,cb} \geq 0$: The empty trip distance from job *ca* to job *cb*; $ca \in JJ$, $cb \in JJ$, $ca \neq cb$.

$\lambda_z \geq 0$: The processing distance of group *z*; $z \in GP$.

w_{ca} : The starting time of job *ca*; $ca \in JJ$.

t_{ca} : The processing time job *ca*; $ca \in JJ$.

$s_{ca,cb}$: The empty travel time from job *ca* to job *cb*; $ca \in JJ$, $cb \in JJ$, $ca \neq cb$.

The model is formulated as follows:

[P^{LAE}]: Minimize: $$Z^{Tru} = GN \cdot \sum_{z \in GP} \lambda_z + \sum_{ca \in JJ} \sum_{cb \in JJ, ca \neq cb} y_{ca,cb} \cdot \tau_{ca,cb} \tag{7.3}$$

Subject to:

$$\sum_{k\in K} x_{z,k} = 1 \qquad \forall z\in GP \tag{7.4}$$

$$\mu_{z,i,j}\cdot x_{z,k} \le \varphi_{j,k} \ \forall i,j\in V,\ i\ne j,\ \forall k\in K, \qquad \forall z\in GP \tag{7.5}$$

$$\sum_{i\in V, i\ne j}\sum_{z\in GP} GN\cdot \mu_{z,i,j}\cdot x_{z,k} - M\cdot(1-\varphi_{j,k}) \le BV \ \forall j\in V, \qquad \forall k\in K \tag{7.6}$$

$$\lambda_z = \sum_{b\in B}\sum_{k\in K}\psi^S_{z,b}\cdot x_{z,k}\cdot D^U_{k,b} + \sum_{b\in B}\sum_{k\in K}\psi^E_{z,b}\cdot x_{z,k}\cdot D^L_{k,b} \qquad \forall z\in GP \tag{7.7}$$

$$\sum_{ca\in JS, ca\ne cb} y_{ca,cb} = 1 \qquad \forall cb\in JJ \tag{7.8}$$

$$\sum_{cb\in JE, ca\ne cb} y_{ca,cb} = 1 \qquad \forall ca\in JJ \tag{7.9}$$

$$\sum_{cb\in JE} y_{ds,cb} = TN \tag{7.10}$$

$$\sum_{ca\in JS} y_{ca,de} = TN \tag{7.11}$$

$$\tau_{ca,cb} = \sum_{z\in GP}\sum_{z'\in GP}\sum_{b\in B}\sum_{k\in K} ld_{z,ca}\cdot\psi^E_{z,b}\cdot ld_{z',cb}\cdot x_{z',k}\cdot D^U_{k,b} \ \forall ca\in JA, \forall cb\in JA,\ ca\ne cb \tag{7.12}$$

$$\tau_{ca,cb} = \sum_{z\in GP}\sum_{z'\in GP, z\ne z'}\sum_{b\in B}\sum_{b'\in B} ld_{z,ca}\cdot\psi^E_{z,b}\cdot ud_{z',cb}\cdot\psi^S_{z',b'}\cdot D^B_{b,b'} \ \forall ca\in JA,\ \forall cb\in JB \tag{7.13}$$

$$\tau_{ca,cb} = \sum_{z\in GP}\sum_{z'\in GP,}\sum_{k\in K}\sum_{k'\in K} ud_{z,ca}\cdot x_{z,k}\cdot ld_{z',cb}\cdot x_{z',k'}\cdot D^K_{k,k'} \ \forall ca\in JB,\ \forall cb\in JA \tag{7.14}$$

$$\tau_{ca,cb} = \sum_{z\in GP}\sum_{z'\in GP,}\sum_{b\in B}\sum_{k\in K} ld_{z,ca}\cdot x_{z,k}\cdot ud_{z',cb}\cdot\psi^S_{z',b}\cdot D^L_{k,b} \ \forall ca\in JB, \forall cb\in JB, ca\ne cb \tag{7.15}$$

$$w_{cb} + M\cdot(1-y_{ca,cb}) \ge w_{ca} + t_{ca} + s_{ca,cb} \qquad \forall ca\in JS, \forall cb\in JE \tag{7.16}$$

$$\sum_{ca \in JA} ld_{z,ca} \cdot w_{ca} \geq \sum_{cb \in JB} ud_{z,cb} \cdot (w_{cb} + t_{cb}) \qquad \forall z \in GP \qquad (7.17)$$

$$t_{ca} = (\sum_{z \in GP} \sum_{b \in B} \sum_{k \in K} ld_{z,ca} \cdot \psi^S_{z,b} \cdot x_{z,k} \cdot D^U_{k,b} + \sum_{z \in GP} \sum_{b \in B} \sum_{k \in K} ud_{z,ca} \cdot \psi^E_{z,b} \cdot x_{z,k} \cdot D^L_{k,b}) / spe$$

$$\forall ca \in JJ \qquad (7.18)$$

$$s_{ca,cb} = \tau_{ca,cb} / spe \qquad \forall ca \in JJ, \forall cb \in JJ, ca \neq cb \qquad (7.19)$$

$$x_{z,k} \in \{0,1\} \qquad \forall z \in GP, \ \forall k \in K \qquad (7.20)$$

$$y_{ca,cb} \in \{0,1\} \qquad \forall ca \in JS, \ \forall cb \in JE \qquad (7.21)$$

$$\tau_{ca,cb} \geq 0 \qquad \forall ca \in JJ, \ \forall cb \in JJ \qquad (7.22)$$

$$\lambda_z \geq 0 \qquad \forall z \in GP \qquad (7.23)$$

Objective (7.3) is to minimize the total travel distance of the yard trucks. Constraints (7.4) ensure that each group of containers is allocated to only one sub-block. Constraints (7.5) guarantee that if container group z is transshipped from vessel i to vessel j, group z can only be allocated a sub-block reserved for vessel j. Constraints (7.6) ensure that the total load of each sub-block must not exceed its capacity. Constraints (7.7) calculate the processing distance of each group. Constraints (7.8) and (7.9) guarantee a one-to-one assignment for each yard truck. Constraints (7.10) and (7.11) give the relationship between dummy jobs and yard trucks. Constraints (7.12) to (7.15) calculate the empty trip distance of each group under different conditions. Constraints (7.16) give the relationship of the starting time of a job and that of its successor. Constraints (7.17) ensure that the unloading job is processed before the loading job of a group. Constraints (7.18) and (7.19) calculate the processing time and empty travel time of each job. Constraints (7.20) to (7.23) define variables.

7.3.2 Linearization

Some of the above functions are nonlinear and the model needs to be linearized. To linearize the nonlinear forms in the objective, i.e. $y_{\text{ca,cb}} \cdot \tau_{\text{ca,cb}}$, a new decision variable is defined as $\kappa_{\text{ca,cb}}$.

Then, the objective function can be rewritten as:

Minimize: $Z^{Tru} = GN \cdot \sum_{z \in GP} \lambda_z + \sum_{ca \in JJ} \sum_{cb \in JJ, ca \neq cb} \kappa_{ca,cb}$ (7.24)

Additional constraints also need to be added:

$$\kappa_{ca,cb} \geq y_{ca,cb} + \tau_{ca,cb} - 1 - M \cdot (1 - y_{ca,cb}) \qquad \forall ca \in JJ,\ \forall cb \in JJ \qquad (7.25)$$

$$\kappa_{ca,cb} \leq M \cdot y_{ca,cb} \qquad \forall ca \in JJ,\ \forall cb \in JJ \qquad (7.26)$$

$$\kappa_{ca,cb} \geq 0 \qquad \forall ca \in JJ,\ \forall cb \in JJ \qquad (7.27)$$

Constraints (7.25) and (7.26) guarantee that $\kappa_{\mathrm{ca,cb}}$ equals to zero, when $y_{ca,cb}$ equals zero, and $\kappa_{\mathrm{ca,cb}}$ equals $\tau_{ca,cb}$ when $y_{ca,cb}$ equals to one. Constraints (7.27) define the variables.

To linearize the nonlinear forms in constraints (7.14), one more decision variable and constraint is added:

$\Delta^{C}_{z,k,z',k'} \in \{0,1\}$: set to one if the empty trip is between group z and group z' and from sub-block k to sub-block k', and zero otherwise; z', $z \in GP$, k', $k \in K$.

Then, three more constraints should be added:

$$\tau_{ca,cb} = \sum_{z \in GP} \sum_{z' \in GP,} \sum_{k \in K} \sum_{k' \in K} ud_{z,ca} \cdot \Delta^{C}_{z,k,z',k'} \cdot ld_{z',cb} \cdot D^{K}_{k,k'} \qquad \forall ca \in JB,\ \forall cb \in JA \qquad (7.28)$$

$$\Delta^{C}_{z,k,z',k'} \geq x_{z,k} + x_{z'k'} - 1 \qquad \forall z, z' \in GP \quad z \neq z',\ \forall k, k' \in K \qquad (7.29)$$

$$\Delta^{C}_{z,k,z',k'} \in \{0,1\}\ \forall z, z' \in GP \quad z \neq z', \qquad \forall k, k' \in K \qquad (7.30)$$

The linearized mathematical model can be formulated as objective (7.24); subject to constraints (7.4) - (7.13); (7.15) - (7.23); (7.25) - (7.30).

7.4 Solution Approach

The formulated mathematical model is too complicated to solve by commercial software (e.g. CPLEX and LINGO). Thus, a decomposition iterative algorithm (DIA) is proposed for the solution of large-scale instances. The DIA is composed of three stages and in order to implement the DIA, the model P^{LAE} is decomposed into two models, P^L and P^E. In the first stage, model P^L is solved for the storage allocation for each group of containers. In the second stage, given the storage locations variables of all groups, model P^E is solved to obtain yard truck scheduling-related decision variables. In the third stage, the above storage location and yard truck scheduling variables are refined by an iterative process, which means the truck scheduling is fixed to optimize the storage allocation for transhipment containers, and with the improved storage locations, yard truck scheduling is optimized. The iterative process will not stop until the stop condition is achieved.

The P^L model solves the transhipment containers storage space allocation. The model P^L is created as:

Input data: all the input data from model P^{LAE}

$[P^L]$: Minimize: $$Z^{TruL} = GN \cdot \sum_{z \in GP} \lambda_z \tag{7.31}$$

Subject to: constraints (7.4) - (7.7); (7.20); (7.23)

The P^E model solves the job processing sequence by yard trucks. The model P^E is formulated as:

Input data: all the input data from model P^{LAE}, and $x_{z,k}$, $\forall z \in GP$, $\forall k \in K$

[P^E]: Minimize: $Z^{TruE} = \sum_{ca \in JJ} \sum_{cb \in JJ, ca \neq cb} \kappa_{ca,cb}$ (7.32)

Subject to: constraints (7.8) - (7.13); (7.15) - (7.19); (7.21); (7.22); (7.25) - (7.30)

The above model is solved by an iteration process, as shown in the *Algorithm.* In the proposed algorithm, the job assignment for each yard truck is fixed to optimize the storage allocation for the containers, and then the job assignment for each yard truck is optimized after the improved storage allocation for containers is obtained. An integer ***N*** is used for controlling the iteration process. After the iteration process, a good solution is obtained. All the aforementioned models, i.e. [P^L], [P^E] and [P^{LAE}], are solved by using CPLEX.

Algorithm**:** input is ***N*** **= 1**; output is a solution for transhipment containers storage allocation and job assignment for each yard truck.

Solve model [P^L];

Do {

Solve model [P^E];

Solve model [P^{LAE}]; //If no improvement achieved, set ***N*** = **0**;

} While (*N* = 1)

Note that the proposed heuristic algorithm evidently reduces the computational complexity of the model, and then outputs a result. It is should be mentioned that the result obtained from the proposed algorithm may lose optimality during the iterative process. However, the trade-off between solution quality and calculation speed can be balanced by controlling the group volume. A more precise solution can be obtained when the group volume is smaller, and vice versa.

7.5 Numerical Experiments

In this section, some computational experiments are conducted to evaluate the performance of the proposed algorithm. The mathematical models presented in the proposed algorithm are coded and solved by CPLEX 12.4 (NetBeans IDE 7.4, Java 8) on a PC (Intel Core i7-2600, 3.4 GHz; Memory, 8 GB).

7.5.1 Description of Instances

In this study, a fixed series of instances are considered, as shown in Table 7.1. The number of transhipment containers from vessel i to vessel j is randomly generated. Also, a vessel may travel to a few container depots or hubs during transportation. For the aforementioned two reasons, assumptions are made on the number of transhipment containers, as shown in Table 7.1.

Table 7.1 Instances generating criteria

Number of vessels	Quay length (m)	Number of yard trucks	Number of sub-blocks	Range of the number of transhipment containers
15	500	20	80	[5000, 8000]
20	700	25	120	[8000, 11000]
30	1100	30	160	[11000, 15000]
40	1500	35	240	[15000, 19000]
50	1800	40	300	[19000, 24000]

The yard configurations are the same as in Zhen *et al*. (2011a), as shown in Figure 7.3. The volume of each sub-block is 240 TEUs. A sub-block has a length of 8 TEUs and the width of a sub-block is 6 TEUs. The horizontal passing lane is unidirectional and the perpendicular passing lane is bidirectional, as shown in Figure 7.1. The width of the passing lanes is set at 30m.

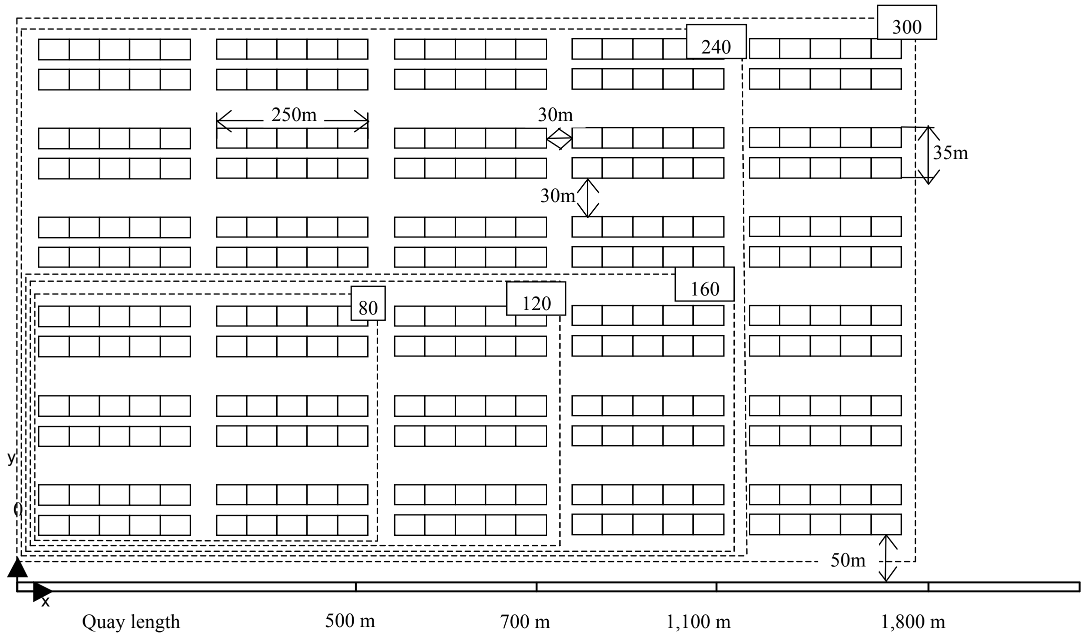

Figure 7.3 Yard layout for instances (source: Zhen *et al.* 2011a)

According to the yard layout, the distance between the berth and yard is known and some of the distance data is shown in Table 7.2 as an example.

Table 7.2 Partial distance input data

$D^B_{1,1}$=0	$D^K_{1,1}$=0	$D^U_{1,1}$=50	$D^L_{1,1}$=50
$D^B_{1,2}$=50	$D^K_{1,2}$=50	$D^U_{1,2}$=100	$D^L_{1,2}$=100
$D^B_{1,3}$=100	$D^K_{1,3}$=100	$D^U_{1,3}$=150	$D^L_{1,3}$=150
$D^B_{1,4}$=150	$D^K_{1,4}$=150	$D^U_{1,4}$=200	$D^L_{1,4}$=200
$D^B_{1,5}$=200	$D^K_{1,5}$=200	$D^U_{1,5}$=250	$D^L_{1,5}$=250
$D^B_{1,6}$=250	$D^K_{1,6}$=485	$D^U_{1,6}$=85	$D^L_{1,6}$=300
$D^B_{1,7}$=300	$D^K_{1,7}$=535	$D^U_{1,7}$=135	$D^L_{1,7}$=350
$D^B_{1,8}$=350	$D^K_{1,8}$=585	$D^U_{1,8}$=185	$D^L_{1,8}$=400
$D^B_{1,9}$=400	$D^K_{1,9}$=635	$D^U_{1,9}$=235	$D^L_{1,9}$=450
$D^B_{1,10}$=450	$D^K_{1,10}$=685	$D^U_{1,10}$=285	$D^L_{1,10}$=500

7.5.2 Results and Comparison

The two series of experiments are designed to illustrate the importance of the proposed enriched transhipment container transport and storage planning model. In one set of experiments, the proposed model is compared with the planning model that takes no account of the group of containers concept. In the other set of experiments, the proposed model is compared with some common used planning strategies.

To evaluate the performance of the proposed heuristic algorithm, the proposed algorithm needs to be compared with the optimal result. However, due to the complexity of the proposed algorithm, CPLEX cannot achieve a result within ten hours even in small scale instances (e.g. 100 groups, 80 sub-blocks, 20 yard trucks, 15 vessels.). Thus, an average travel distance (ATD) is used for comparison. The calculation heuristic of the ATD is the same as Zhen *et al*. (2011a). The ATD is the average laden trips plus the empty trips of the yard trucks. In order to show all the results concisely, all the results are multiplied by 10^{-6}.

As a number of transhipment containers are grouped with the same arriving and departing vessel, more detailed planning is obtained if the volume of the group is smaller. The volume of a group is changed in the five series of instances where a series contains five instances, as shown in Table 7.3(a-e). Since more jobs are considered, the computational time becomes larger when group volume becomes smaller.

Table 7.3a Results and computational time of different group sizes

Instances	ID no.	ATD	Number of containers in a group							
			10		20		40		60	
			Z^{Tru}	Time (min)	Z^{Tru}	Time (min)	Z^{Tru}	Time (min)	Z^{Tru}	Time (min)
15 vessels	15-1	23.2	4.69	27	4.77	22	4.83	19	4.87	17
	15-2	25.6	4.63	27	4.67	19	4.69	15	4.75	14
	15-3	22.1	4.61	26	4.68	19	4.75	17	4.79	14
	15-4	27.5	5.11	33	5.24	26	5.43	20	5.55	16
	15-5	29.0	5.02	29	5.17	23	5.28	18	5.39	17

Table 7.3b Results and computational time of different group sizes

Instances	ID no.	ATD	Number of containers in a group							
			10		20		40		60	
			Z^{Tru}	Time (min)	Z^{Tru}	Time (min)	Z^{Tru}	Time (min)	Z^{Tru}	Time (min)
20 vessels	20-1	44.7	5.79	51	5.94	43	6.07	35	6.12	31
	20-2	42.3	5.96	50	6.07	41	6.19	35	6.26	29
	20-3	47.4	5.84	55	6.11	45	6.20	34	6.26	28
	20-4	53.2	6.15	52	6.24	46	6.33	36	6.40	30
	20-5	55.7	6.13	61	6.33	52	6.39	44	6.44	36

Table 7.3c Results and computational time of different group sizes

Instances	ID no.	ATD	Number of containers in a group							
			10		20		40		60	
			Z^{Tru}	Time (min)	Z^{Tru}	Time (min)	Z^{Tru}	Time (min)	Z^{Tru}	Time (min)
30 vessels	30-1	56.3	9.81	315	9.85	223	9.92	167	9.96	100
	30-2	60.1	9.65	337	9.71	214	9.78	155	9.83	104
	30-3	58.6	9.74	272	9.69	186	9.63	138	9.57	93
	30-4	62.2	9.22	286	9.17	207	9.10	163	9.04	111
	30-5	59.0	9.01	247	9.08	192	9.13	140	9.19	96

Table 7.3d Results and computational time of different group sizes

Instances	ID no.	ATD	Number of containers in a group							
			10		20		40		60	
			Z^{Tru}	Time (min)	Z^{Tru}	Time (min)	Z^{Tru}	Time (min)	Z^{Tru}	Time (min)
40 vessels	40-1	70.6	9.55	389	10.00	350	11.5	311	13.8	291
	40-2	73.3	9.21	442	9.82	396	10.1	357	12.7	327
	40-3	68.9	8.03	417	8.36	384	8.6	341	11.9	316
	40-4	71.7	8.47	375	8.91	326	10.4	279	13.0	243
	40-5	74.5	9.38	410	9.93	371	11.8	335	13.5	303

Table 7.3e Results and computational time of different group sizes

Instances	ID no.	ATD	Number of containers in a group							
			10		20		40		60	
			Z^{Tru}	Time (min)	Z^{Tru}	Time (min)	Z^{Tru}	Time (min)	Z^{Tru}	Time (min)
50 vessels	50-1	90.3	----	*	----	*	37.3	674	43.9	642
	50-2	90.7	----	*	----	*	36.2	601	42.1	587
	50-3	85.0	----	*	----	*	31.9	656	37.5	613
	50-4	91.6	----	*	----	*	32.5	679	38.6	626
	50-5	93.5	----	*	----	*	41.1	691	48.3	640

Since increasing the group volume significantly increases the number of jobs, when the group volume becomes smaller, the computer needs longer time to obtain a result. When the group volume becomes smaller, the number of jobs becomes larger and more specific locations are calculated. Hence, the objective becomes a little smaller as long as the group volume becomes smaller. Compared to the ATD obtained from other research methodologies, the proposed model can obtain a better result. Consideration of storage assignment for transhipment containers and yard truck travel routes evidently reduces the truck travel distance, and it will assist transhipment terminals in improving operation efficiency. Considering the computational time, instances with a group volume of 20 are chosen to make comparison between the proposed heuristic method and other methods, as shown in Table 7.4.

Table 7.4 Yard truck traveling distance using different strategies

Instances ID.	Heuristic method		Strategy One		Strategy Two	
	Z^{Tru}	Time (min)	Z^{Tru}	Time (min)	Z^{Tru}	Time (min)
15-1	4.77	22	6.46	2	6.46	2
15-2	4.67	19	6.12	2	6.35	2
15-3	4.68	19	7.28	2	7.17	2
15-4	5.24	26	7.65	2	7.33	2
15-5	5.17	23	6.94	2	6.91	2
20-1	5.94	43	9.15	4	8.83	4
20-2	6.07	41	9.43	4	9.29	4
20-3	6.11	45	9.61	4	9.66	5
20-4	6.24	46	9.57	5	9.72	5
20-5	6.33	52	9.62	5	9.78	5
30-1	9.85	43	74.1	11	76.5	10
30-2	9.71	214	82.9	10	79.1	9
30-3	9.69	186	81.3	11	84.5	11
30-4	9.17	207	73.3	12	75.7	12
30-5	9.08	192	76.5	11	74.0	11
40-1	10.0	389	105	34	111	35
40-2	9.82	442	101	33	123	32
40-3	8.36	417	95.3	30	92.4	33
40-4	8.91	375	94.1	30	90.7	30
40-5	9.93	410	130	31	98.4	30

Two other planning strategies are employed to evaluate the performance of the proposed heuristic method. In strategy one, a transhipment container is stored in a location which is the nearest place to the arriving vessel. In strategy two, a transhipment container is stored in a location which is the nearest place to the departing vessel. These two strategies are commonly used in transhipment hubs. When the instance size is small, the two planning strategies are able to obtain good results, as in the proposed algorithm. However, the two planning strategies achieve much worse results than the proposed algorithm when the problem size is large. Therefore, a conclusion can be drawn that the empty travel distance influences the total travel distance and is an essential part of yard template planning. The accurate calculation of the yard truck travel route can reduce the travel distance and help container terminals improve operation efficiency. The comparisons between the proposed heuristic method and other two strategies also show that the proposed method can obtain much better solutions than other strategies, but that more computational time is needed. As the shipping information is always obtained in advance, it is more important for terminal managers to have better planning. Hence, although the proposed method takes a longer time to achieve a better result, it is more applicable in practice.

7.6 Summary

The operation optimization of transhipment container terminals is different from gateway terminals as the issues in a transhipment terminal are more complicated. Some researchers have studied the integration problem occurring in transhipment terminals in both the yard side and quayside. This chapter describes comprehensive operations in transhipment container transportation based on previous studies. The proposed model can be linked with the model by Zhen *et al.* (2011a) for the quayside, and mathematically integrates yard truck routing and transhipment container storage allocation. Containers that have the same departing vessel and the same arriving vessel, are grouped to simply the calculation process. A heuristic method is proposed for the solution. The results show that group volume influences both computational time and objective value. Two yard planning strategies are introduced for comparison with the proposed heuristic method, and it was found that the proposed method can obtain a better solution in a reasonable time.

Chapter 8 Conclusions and Suggestions for Future Research

8.1. Conclusions

With the increasing development of containerized cargo, terminal companies devote enormous time and resources to increasing terminal throughput. One straightforward approach is to build more container terminals; however, this is practically impossible for some land scarce regions, such as in Asia, where additional land is simply too expensive. Thus, firms prefer to increase the terminal throughput by more productive operations. Internal tractors assignment and scheduling is one of the most critical and challenging issues. A good scheduling strategy can help firms optimize container transport schedules leading to improvement of throughput.

In recent decades, internal tractors assignment and scheduling (ITAS) has attracted the attention of researchers. Investigation of ITAS starts from a single decision problem, such as the SAP and ITs scheduling problem, and moves forward to the integration of multiple decision problems. However, the existing published works for ITAS are still incomplete. Therefore, ITAS was studied holistically by investigating the scheduling and assignment of internal tractors in both gateway hubs and transhipment terminals.

Internal tractors scheduling and assignment are essential operations of both gateway and transhipment container terminal systems. ITAS has a strong influence on terminal performance, such as terminal productivity, equipment utilization, and container throughput. To ensure customer satisfaction and economic benefits for the terminal, well-designed internal tractors scheduling and assignment plays a critical role in a container terminal system. However, the container delivery operation is different in gateway and transhipment terminals. The major operation of a gateway port is importing and exporting containers, whereas the major activity of a transhipment hub is transshipping containers from one vessel to another. Thus, ITAS cannot be solved using the same method for these two kinds of terminal.

In this connection, ITAS is firstly solved for the gateway terminal situation, as discussed in Chapters 4 and 5. In Chapter 4, a model is proposed to schedule yard trucks to perform a number of loading and unloading jobs, and to allocate storage locations for inbound containers with consideration of all available storage locations in the terminal. To solve the complicated model, a hybrid GA is proposed. In the proposed GA, a guidance mutation approach and an exhaustive heuristic for local searching are used in order to force the GA to converge faster and be steadier. For the sake of comparison, a simple GA approach and other heuristic algorithms are also implemented in the solution. The experimental results indicate that the proposed hybrid GA approach is able to obtain a better solution compared with the simple GA and other heuristic approaches. In Chapter 5, ITAS is further studied with the aim of determining yard truck deployment strategy with consideration of the yard truck scheduling and storage space assignment discussed in Chapter 4. It not only concerns single day container delivery operations, but also considers the long-term terminal efficiency when the yard trucks are deployed in both self-owning and rented modes. To deal with this issue, a TLH approach is developed, in which the problem is decomposed into two levels. The first level determines the daily operations of internal trucks, while the second level determines the truck deployment strategy based on calculations in the first level. The experimental results show that the proposed method can achieve a better yard truck deployment strategy and assignment schedule than other commonly applied methods.

In Chapters 6 and 7, ITAS is studied in transhipment hubs. The first aspect of transhipment container delivery in transhipment hubs is to find a location for the temporary storage of a transhipment container, as discussed in Chapter 6. Modeled as a linear mathematical model, it can be solved by using linear programming. In Chapter 7, it is further extended to schedule yard trucks to perform all the transhipment jobs considering the issue investigated in Chapter 6. The problem is too complicated to solve by commercial software; thus, a decomposition iterative algorithm is developed. The proposed methodology involves three stages. In the first stage, the storage allocation for each group of containers is determined. In the second stage, given the storage location variables of all groups, truck scheduling is obtained. In the third stage, the above storage location and yard truck scheduling is refined by an iterative process, which means that with the truck scheduling fixed, the storage allocation for the transhipment containers is optimized, and with the improved storage locations, the yard truck scheduling is optimized. To compare the proposed methodology, another two yard planning strategies are also implemented. The experimental results demonstrate that the group volume influences both the computational time and the objective value, and show that the proposed methodology can obtain a better solution that other yard planning strategies in a reasonable time

8.2 Limitations and Suggestions for Future Work

8.2.1 Assumption of Deterministic Assignment and Scheduling Problem

In this study, all ITAS is deterministic. The numerical data, such as the amount and different of kinds of equipment, are assumed to be known in advance. However, in a real situation, the uncertainty of how to act regarding container delivery and transportation is quite common. For example, in container transportation, new information for yard trucks, such as truck breakdown and congestion, arises frequently. Previously feasible truck scheduling and storage allocation may become infeasible and require rescheduling. Therefore, an optimization methodology that can deal with a rapidly changing situation is necessary. In future research, a dynamic model that considers flexibility of the schedule and assignment is required for terminal operations.

8.2.2 Extension of Current Modeling

Container terminals are complicated systems, which contain a large number of operations for container delivery and transportation. However, this study only considers partial operations in terminals. It provides a good solution for a sub-problem, but a good solution for an entire system is not guaranteed.

Further studies could expand the model developed in this research by separating it into two categories. The first category considers more detailed practical issues. For example, the model developed in this research only considers one layer of containers located in the yard. Realistically however, a stack usually consist of more than one layer, for example, terminals in Hong Kong always stack containers in more than three layers, and, as a result, re-handling occurs. According to Zhao and Goodchild (2010), truck arrival time has a relationship to container re-handling. The combination of storage allocation, truck arrival time and container re-handling should be investigated in future related studies.

The second category integrates other operations in container terminals. For example, according to Petering (2010), a yard truck control system based on quay crane priority, yields a higher gross crane rate than a system based on container due times. Moreover, as quay crane priority is related to the precedence constraints of outbound containers (Xue *et al*., 2013), integration with quay crane loading should be considered in future related studies.

8.2.3 Solution Approach with Better Efficiency

In this study, ITAS is formulated as mathematical models and solved by heuristic algorithms or linear programming. Although the proposed heuristic algorithms in Chapters 4, 5, and 7 can solve real word large problem size data, the solution takes hours and the optimal solution is not guaranteed. Another direction of future research is to design algorithms that can provide optimal solutions in a shorter period of time.

Appendix 1 Problem Sets in Chapter 4

Information of 100 job instances: earliest possible time follows exponential distribution and due time follows uniform distribution.

Information of 60 loading jobs

ID	Origin X	Origin Y	Destination X	Destination Y	Time Window A	Time Window B
1	1052	733	1009	1080	78	411
2	720	5	971	1220	483	802
3	1360	352	901	319	455	694
4	746	759	63	47	573	852
5	1462	674	142	442	110	481
6	425	1392	173	478	34	384
7	386	1159	99	1366	291	633
8	1360	597	898	1007	73	559
9	263	1122	598	88	226	706
10	21	229	419	37	277	567
11	193	258	602	1368	47	335
12	794	952	469	985	1368	1621
13	64	380	437	30	372	720
14	7	1402	611	855	89	312
15	1382	678	339	4	850	1053
16	1199	403	1375	802	530	993
17	253	30	1058	1161	48	390
18	425	820	1244	510	144	386
19	477	307	5	1032	1002	1212
20	454	1257	944	1438	241	707
21	358	1203	994	238	1782	2251
22	303	745	1482	1083	12	342
23	1313	352	1452	373	40	262
24	1230	1481	467	497	187	395
25	60	939	1164	668	1019	1326
26	1486	1497	339	774	404	726

27	1222	600	1499	497	57	430
28	392	391	282	588	95	337
29	1026	1155	870	221	200	664
30	1092	892	816	232	596	977
31	885	199	1156	467	196	478
32	171	155	787	816	259	654
33	1091	1128	202	1192	395	885
34	733	159	1278	964	836	1233
35	75	530	1097	1330	318	539
36	437	530	1326	1428	327	655
37	200	248	890	427	38	288
38	1008	456	674	566	142	497
39	375	1131	1114	956	89	500
40	749	1145	1262	1031	91	585
41	403	702	1009	957	85	522
42	1139	1458	1130	396	1236	1488
43	363	1020	653	767	101	588
44	773	494	423	708	295	570
45	566	103	335	415	264	640
46	16	402	780	1162	837	1090
47	605	107	897	711	287	589
48	1491	713	1009	1188	468	845
49	329	462	501	232	47	398
50	1284	817	101	1317	34	454
51	182	290	260	1165	203	555
52	1031	548	1387	631	304	695
53	1222	278	1001	528	116	578
54	1462	60	369	1474	2738	2989
55	1347	198	1001	872	83	542
56	305	1323	1093	962	667	928
57	737	1384	1449	1459	61	445
58	493	142	265	475	895	1102
59	299	403	73	1364	756	978
60	1028	98	748	1049	822	1140

Information of 40 unloading jobs

ID	Origin X	Origin Y	Time Window A	Time Window B
61	707	430	109	519
62	1201	141	96	548
63	494	685	1524	1933
64	1032	802	75	539
65	362	236	415	800
66	650	260	693	921
67	958	764	1422	1884
68	1034	983	487	965
69	24	793	520	959
70	37	496	1592	1823
71	383	1481	129	415
72	782	932	494	929
73	644	7	664	1026
74	69	1380	521	746
75	398	453	336	717
76	467	198	461	710
77	925	771	304	692
78	1048	1090	908	1268
79	0	287	826	1166
80	948	253	275	732
81	772	277	200	446
82	302	1360	430	758
83	313	1330	531	999
84	953	990	1439	1860
85	441	637	192	623
86	261	949	829	1322
87	633	388	744	982
88	1309	590	48	300
89	920	1209	321	655
90	1302	906	4	385
91	500	972	541	792
92	1031	716	376	740
93	955	891	277	515
94	372	1247	347	554
95	380	560	866	1204
96	446	1303	108	598

97	14	45	501	954
98	265	543	595	992
99	1443	180	389	705
100	1440	1145	121	451

Information of 100 available storage locations

ID	X	Y	ID	X	Y
1	1318	267	51	263	174
2	1386	1044	52	1336	777
3	615	1015	53	601	485
4	725	5	54	124	383
5	755	140	55	902	441
6	969	821	56	929	1395
7	1356	1250	57	438	134
8	978	1101	58	1035	381
9	785	887	59	1132	878
10	173	817	60	982	249
11	1020	155	61	591	834
12	152	674	62	1119	774
13	452	1036	63	611	794
14	710	125	64	381	1184
15	1262	1053	65	1020	1299
16	1322	900	66	1079	1180
17	192	953	67	811	1170
18	1226	892	68	747	318
19	456	411	69	339	36
20	393	1147	70	1424	581
21	766	612	71	1084	1209
22	902	28	72	617	1380
23	6	1202	73	1364	111
24	951	857	74	125	1486
25	1403	1357	75	1206	1040
26	1051	1026	76	1344	122
27	188	653	77	85	304
28	280	118	78	718	573
29	1154	537	79	1124	1141
30	1370	1138	80	533	1224
31	252	1472	81	1469	928

32	334	1341	82	873	931
33	388	1305	83	1015	1460
34	1316	1016	84	214	999
35	1386	1498	85	885	449
36	379	865	86	812	399
37	1221	207	87	616	552
38	1026	309	88	318	73
39	1015	1116	89	813	1446
40	367	146	90	823	854
41	19	1107	91	198	1451
42	1007	90	92	889	1102
43	283	653	93	873	1288
44	976	595	94	1008	1200
45	42	810	95	1376	1349
46	235	341	96	867	933
47	443	819	97	84	313
48	154	492	98	272	171
49	609	199	99	389	1061
50	180	617	100	1127	536

Appendix 2 Problem Sets in Chapter 5

Example of the amount of containers and storage locations in each day of a year.

Day	Number of Loading Jobs	Number Of Unloading Jobs	Number of Storage Locations
1	5598	5202	6902
2	5220	4112	7280
3	5281	5492	7219
4	5725	4363	6775
5	4523	4253	7977
6	4685	4855	7815
7	4952	5877	7548
8	4711	4819	7789
9	4859	5352	7641
10	5586	5327	6914
11	5064	3876	7436
12	3861	4134	8639
13	5838	4410	6662
14	4078	4181	8422
15	5711	4456	6789
16	4908	4116	7592
17	5762	4260	6738
18	5374	5318	7126
19	4459	5968	8041
20	4473	5581	8027
21	5020	5954	7480
22	4959	4071	7541
23	4006	5604	8494
24	5134	4859	7366
25	4123	4658	8377
26	4023	5857	8477
27	4962	5731	7538
28	5163	3261	7337
29	3710	5092	8790
30	5943	4688	6557
31	7289	5673	5811
32	3963	4641	8537
33	3405	5717	9095

34	4240	4168	8260
35	3949	4021	8551
36	4677	4913	7823
37	4882	3956	7618
38	4682	4536	7818
39	3583	4900	8917
40	4514	4450	7986
41	4344	4434	8156
42	4245	4480	8255
43	4234	3919	8266
44	4578	4177	7922
45	4357	5177	8143
46	4336	5411	8164
47	4702	5094	7798
48	4590	4415	7910
49	5373	4481	7127
50	3344	4516	9156
51	5805	4325	6695
52	5058	4316	7442
53	4133	4765	8367
54	4903	5860	7597
55	4971	4472	7529
56	4033	3916	8467
57	4018	5078	8482
58	4322	4841	8178
59	2559	421	9941
60	3875	4435	8625
61	3828	3640	8672
62	5313	4475	7187
63	6094	3878	6406
64	5582	3574	6918
65	3759	5631	8741
66	5343	5153	7157
67	3935	4409	8565
68	4343	4309	8157
69	4744	4406	7756
70	4991	5188	7509
71	4456	4586	8044
72	4510	4488	7990
73	4333	5429	8167

74	5282	5242	7218
75	6123	6528	6677
76	5038	4985	7462
77	4262	4859	8238
78	5200	5047	7300
79	4439	5897	8061
80	3894	5126	8606
81	4652	3876	7848
82	5203	4750	7297
83	4071	5261	8429
84	4683	5809	7817
85	4873	5739	7627
86	5512	4513	6988
87	4692	6004	7808
88	3797	4911	8703
89	5872	4269	6628
90	7701	5383	5799
91	5257	4737	7243
92	6494	4798	6006
93	5795	4567	6705
94	4130	5386	8370
95	4017	4110	8483
96	4567	5258	7933
97	3327	6035	9173
98	4758	4987	7742
99	4721	5281	7779
100	4826	5013	7674
101	5446	3462	7054
102	4780	5013	7720
103	4627	4883	7873
104	5227	4553	7273
105	4501	4913	7999
106	4296	6474	8204
107	5778	4735	6722
108	5309	4542	7191
109	5211	4989	7289
110	6346	4173	6154
111	5247	4680	7253
112	5023	5628	7477
113	4641	5854	7859

114	4918	4994	7582
115	5103	6069	7397
116	5437	5724	7063
117	4169	4864	8331
118	4450	6232	8050
119	4279	4303	8221
120	5520	4143	6980
121	4946	4165	7554
122	4704	5230	7796
123	4771	6216	7729
124	4737	4390	7763
125	5647	6080	6853
126	5841	5707	6659
127	4778	5126	7722
128	6268	5171	6232
129	4687	4673	7813
130	4243	5650	8257
131	5011	5219	7489
132	4681	5522	7819
133	5027	4310	7473
134	4371	4029	8129
135	4541	4832	7959
136	6460	4899	6040
137	4702	4600	7798
138	4714	5046	7786
139	5721	5365	6779
140	3556	5028	8944
141	5939	6414	6561
142	4109	4729	8391
143	5327	4589	7173
144	5052	5402	7448
145	4375	4738	8125
146	4965	6046	7535
147	5151	5569	7349
148	4608	4425	7892
149	3916	4716	8584
150	5128	5246	7372
151	7024	868	5476
152	4188	4708	8312
153	4916	4672	7584

154	4526	4996	7974
155	4277	4707	8223
156	6271	4934	6229
157	5699	5133	6801
158	4482	4885	8018
159	4854	4965	7646
160	4988	4667	7512
161	4394	5075	8106
162	3980	5155	8520
163	4679	4532	7821
164	4934	5315	7566
165	5534	4918	6966
166	4295	4919	8205
167	4863	5003	7637
168	4464	4127	8036
169	5557	5216	6943
170	4976	5496	7524
171	4271	4730	8229
172	4865	5975	7635
173	5143	3683	7357
174	5063	4047	7437
175	4661	5762	7839
176	3980	4832	8520
177	4062	3892	8438
178	5556	4613	6944
179	5823	5503	6677
180	4415	4714	8085
181	2684	174	9816
182	5395	6059	7105
183	4881	5599	7619
184	4599	5191	7901
185	4774	5362	7726
186	5386	3916	7114
187	4264	4331	8236
188	4125	5286	8375
189	6007	4796	6493
190	4035	4192	8465
191	3361	5727	9139
192	4841	5625	7659
193	3893	5109	8607

194	4251	4591	8249
195	5297	4487	7203
196	5317	4440	7183
197	5445	5439	7055
198	4024	4752	8476
199	4984	4963	7516
200	3638	5347	8862
201	4087	5200	8413
202	5327	5224	7173
203	4846	4239	7654
204	3952	5242	8548
205	5321	4149	7179
206	4633	4240	7867
207	4489	5305	8011
208	5424	6413	7076
209	5123	4505	7377
210	4752	5408	7748
211	5406	4851	7094
212	9923	6012	7577
213	5072	5304	7428
214	4323	4684	8177
215	4668	4790	7832
216	6445	4528	6055
217	4335	4958	8165
218	4525	4016	7975
219	4434	4531	8066
220	4387	4213	8113
221	4358	4825	8142
222	4617	4961	7883
223	5483	4572	7017
224	5015	4701	7485
225	5132	6511	7368
226	4680	4903	7820
227	4477	4819	8023
228	4807	4749	7693
229	3976	4175	8524
230	5058	5819	7442
231	4775	5218	7725
232	4418	3983	8082
233	3832	4702	8668

234	5169	5274	7331
235	5038	4409	7462
236	3664	5870	8836
237	4807	3992	7693
238	5060	5638	7440
239	5808	4034	6692
240	4034	4767	8466
241	5006	4987	7494
242	4910	4189	7590
243	1887	2878	10613
244	5703	4835	6797
245	5436	4108	7064
246	4522	4694	7978
247	5160	4652	7340
248	4875	4465	7625
249	5245	3579	7255
250	4999	5285	7501
251	4712	3796	7788
252	5052	4813	7448
253	4856	4059	7644
254	5454	4267	7046
255	5371	4960	7129
256	4223	4143	8277
257	3872	5463	8628
258	4270	5444	8230
259	3509	5602	8991
260	5136	5561	7364
261	4961	4010	7539
262	4417	6663	8083
263	5398	5184	7102
264	4431	4668	8069
265	6225	4430	6275
266	5650	5565	6850
267	5483	5402	7017
268	5271	4154	7229
269	4406	5117	8094
270	5930	4315	6570
271	5307	4594	7193
272	5465	5360	7035
273	261	8212	12239

274	4466	4089	8034
275	4908	4925	7592
276	4648	5020	7852
277	4552	4410	7948
278	5211	4699	7289
279	3844	4335	8656
280	3822	4638	8678
281	4496	4700	8004
282	4699	4586	7801
283	3588	4533	8912
284	4637	3361	7863
285	5003	4639	7497
286	4331	4380	8169
287	4790	5939	7710
288	4486	5087	8014
289	4737	5003	7763
290	4560	4605	7940
291	4591	5491	7909
292	4089	4837	8411
293	4926	4570	7574
294	6154	5133	6346
295	3939	4102	8561
296	4580	4373	7920
297	4795	3706	7705
298	3911	4946	8589
299	4340	4164	8160
300	4214	5050	8286
301	4184	3672	8316
302	3301	4725	9199
303	3703	3791	8797
304	5295	9891	9905
305	4795	4023	7705
306	4709	4691	7791
307	4095	6225	8405
308	3752	4345	8748
309	4873	4993	7627
310	4407	6430	8093
311	3946	4536	8554
312	4028	4768	8472
313	4817	5215	7683

314	5106	5327	7394
315	4800	3914	7700
316	3370	3916	9130
317	4802	4764	7698
318	4041	4049	8459
319	3576	4418	8924
320	3933	5533	8567
321	5310	6516	7190
322	3797	5114	8703
323	5707	2972	6793
324	3879	5069	8621
325	4501	4303	7999
326	4533	5003	7967
327	4860	3827	7640
328	4231	5351	8269
329	4465	3890	8035
330	4157	4780	8343
331	4980	5123	7520
332	4361	4918	8139
333	3550	5664	8950
334	10419	4523	5081
335	4314	3495	8186
336	5186	5791	7314
337	5533	4981	6967
338	4037	5310	8463
339	4593	4809	7907
340	4131	4815	8369
341	3736	4710	8764
342	3306	4627	9194
343	5160	4569	7340
344	4827	3078	7673
345	4810	5532	7690
346	4195	5413	8305
347	4218	5168	8282
348	4545	4866	7955
349	4535	5726	7965
350	4391	5707	8109
351	5003	4511	7497
352	4791	3619	7709
353	4660	4619	7840

354	5027	5905	7473
355	3715	4522	8785
356	4157	4264	8343
357	5491	4438	7009
358	4927	3872	7573
359	4646	3919	7854
360	5832	4589	6668
361	3917	4031	8583
362	5301	4557	7199
363	4153	5383	8347
364	4997	3973	7503
365	3066	6201	9434

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