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Models and Solutions Algorithms for Improving Operations in Marine Transportation

Maxim A. Dulebenets

MODELS AND SOLUTION ALGORITHMS FOR IMPROVING OPERATIONS IN MARINE TRANSPORTATION

by

Maxim A. Dulebenets

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ABSTRACT

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International seaborne trade rose significantly during the past decades. This created the need to improve efficiency of liner shipping services and marine container terminal operations to meet the growing demand. The objective of this dissertation is to develop simulation and mathematical models that may enhance operations of liner shipping services and marine container terminals, taking into account the main goals of liner shipping companies (e.g., reduce fuel consumption and vessel emissions, ensure on-time arrival to each port of call, provide vessel scheduling strategies that capture sailing time variability, consider variable port handling times, increase profit, etc.) and terminal operators (e.g., decrease turnaround time of vessels, improve terminal productivity without significant capital investments, reduce possible vessel delays and associated penalties, ensure fast recovery in case of natural and man-made disasters, make the terminal competitive, maximize revenues, etc.).

This dissertation proposes and models two alternatives for improving operations of marine container terminals: 1) a floaterm concept and 2) a new contractual agreement between terminal operators. The main difference between floaterm and conventional marine container terminals is that in the former case some of import and/or transshipment containers are handled by off-shore quay cranes and placed on container barges, which are further towed by push boats to assigned feeder vessels or floating yard. According to the new collaborative agreement, a dedicated marine container terminal operator can

divert some of its vessels for the service at a multi-user terminal during specific time windows.

Another part of dissertation focuses on enhancing operations of liner shipping services by introducing the following: 1) a new collaborative agreement between a liner shipping company and terminal operators and 2) a new framework for modeling uncertainty in liner shipping. A new collaborative mechanism assumes that each terminal operator is able to offer a set of handling rates to a liner shipping company, which may result in a substantial total route service cost reduction. The suggested framework for modeling uncertainty is expected to assist liner shipping companies in designing robust vessel schedules.

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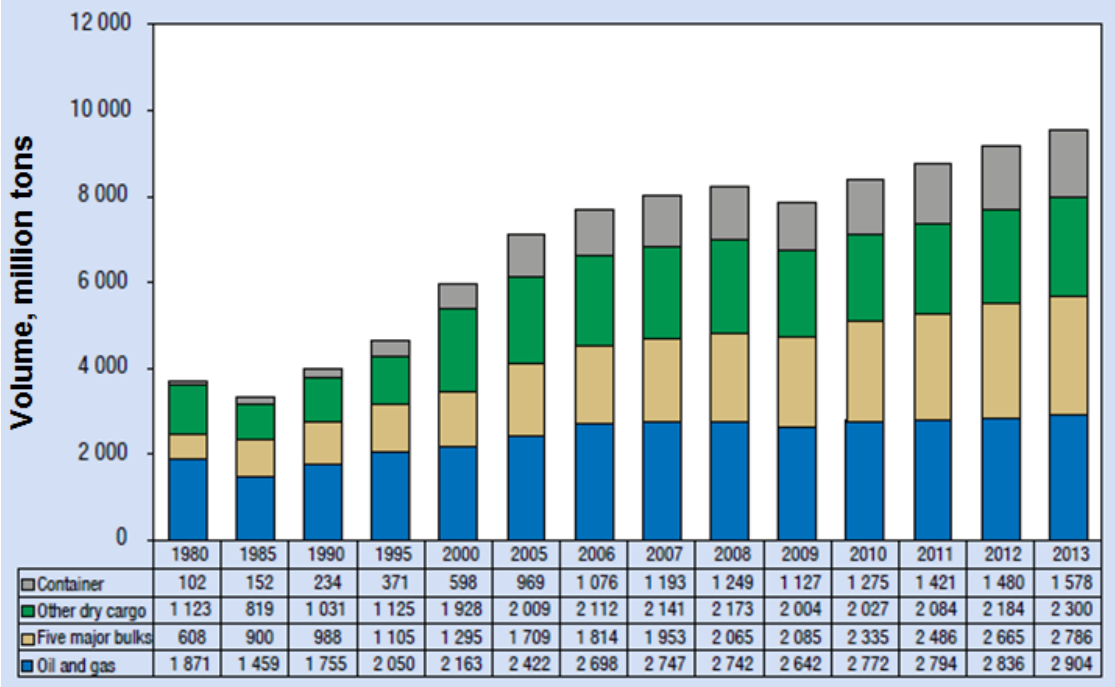
1. INTRODUCTION

Maritime transportation is crucial for the world international trade. The cargo, carried by vessels, comprises more than 80% of the global trade tonnage (UNCTAD, 2014). The international seaborne trade rose by more than 120% by weight from 1980 to 2008 mainly due to increasing standards of living, fast industrialization, population growth, and competitive markets (Umang, Bierlaire, & Vacca, 2011). The volume of all forms of cargo, carried by vessels, and ton-miles significantly increased during last decades. According to statistical data, provided by UNCTAD (2014), a rapid growth in transported amount of dry cargo (+5.3% change in tonnage from 2012 to 2013), containerized cargo (+6.6% in tonnage from 2012 to 2013), and major bulk cargo (+4.5% in tonnage from 2012 to 2013) was observed, while the future growth in the international seaborne trade was also projected for 2014 (see Figure 1).

According to the World Shipping Council (2014), the Port of Shanghai (China) remains the busiest seaport in the world (33.62 million TEUs) with 3.35% trade volume growth between 2012 and 2013 (see Table 1). The second rank is given to the Port of Singapore (with 32.60 million TEUs). Seven out of 10 top container seaports belong to China. All of them demonstrated increasing seaborne trade volumes in 2013, except the port of Hong Kong, which lost 3.45% of business. As for European ports, the Port of Rotterdam (the Netherlands) was in the list of top 10 world container ports in 2011 (the 10th rank with 11.88 million TEUs), but was advanced by the Port of Tianjin (China) in 2012 (12.30 million TEUs vs. 11.87 million TEUs).



	1980	1985	1990	1995	2000	2005	2006	2007	2008	2009	2010	2011	2012	2013
Container	102	152	234	371	598	969	1 076	1 193	1 249	1 127	1 275	1 421	1 480	1 578
Other dry cargo	1 123	819	1 031	1 125	1 928	2 009	2 112	2 141	2 173	2 004	2 027	2 084	2 184	2 300
Five major bulks	608	900	988	1 105	1 295	1 709	1 814	1 953	2 065	2 085	2 335	2 486	2 665	2 786
Oil and gas	1 871	1 459	1 755	2 050	2 163	2 422	2 698	2 747	2 742	2 642	2 772	2 794	2 836	2 904

Figure 1. International Seaborne Trade Trends

Source: UNCTAD (2014)

Table 1

Top 10 World Seaports

Rank	Port, country	Volume, 10^6 TEUs		diff., %
		2013	2012	
1	Shanghai, China	33.62	32.53	**3.35**
2	Singapore, Singapore	32.60	31.65	**3.00**
3	Shenzhen, China	23.28	22.94	**1.48**
4	Hong Kong, China	22.35	23.12	**-3.45**
5	Busan, South Korea	17.69	17.04	**3.81**
6	Ningbo-Zhoushan, China	17.33	16.83	**2.97**
7	Qingdao, China	15.52	14.50	**7.03**
8	Guangzhou Harbor, China	15.31	14.74	**3.87**
9	Jebel Ali, Dubai, UAE	13.64	13.30	**2.56**
10	Tianjin, China	13.01	12.30	**5.77**

Source: World Shipping Council (2014)

The Port of Los Angeles was observed as the busiest U.S. seaport with 7.87 million TEUs in 2012 and 8.08 million TEUs in 2013 (the 19th in the world). The Port of Long Beach remained the second (the 21st in the world) U.S. seaport in 2013 with 6.73 million TEUs. The third rank among U.S. seaports (and the 27th in the world) belongs to the Port of New York/New Jersey with 5.47 million TEUs in 2013. More statistical data about the top 10 container seaports is presented in Table 1.

To meet this growing demand, facing capacity expansion limitations (e.g., lack of land, high cost of expansion, etc.), it is necessary to provide proper planning and management of liner shipping and terminal operations. The following alternatives are mostly used by liner shipping companies: a) deployment of larger vessels, b) slow steaming, and c) alliance agreements. The Journal of Commerce (2013) indicated that "seeking efficiency and economies of scale, the world's container carriers are increasingly ordering megaships capable of handling more than 8,000 20-foot-equivalent container units (TEUs)". However, deployment of larger vessels with higher capacity can add constraints to seaport operations (Mourão, Pato, & Paixão, 2002).

Similarly, the port capacity can be increased by upgrading existing ports or constructing new facilities (McCalla, 1999). Alternative that do not involve construction are based on improvement of conventional equipment and productivity by introducing new forms of technology (Ballis, Golias, & Abakoumkin, 1997), information systems (Henesey, 2004), and work organization (Paixão & Marlow, 2003).

Unlike tramp companies, liner shipping companies have specific routes with a predetermined sequence of ports to be visited (a.k.a., port rotation) and certain frequency of service (Norstad, Fagerholt, & Laporte, 2011; Wang, Alharbi, & Davy, 2014). Each

vessel should arrive to the port of call within a set time window (TW). However, port congestion may substantially disrupt schedules of liner shipping companies. According to the Journal of Commerce (2014), “ports in Oman, the Philippines, India, the U.S., Hong Kong and Netherlands are facing congestion surcharges. European shippers are urging container lines to reduce the surcharges and include them in a single negotiable rate when possible”.

Container terminal operations can be divided into: 1) seaside operations, 2) storage yard operations, and 3) landside operations. Seaside operations deal with berthing of vessels, stowage planning, quay crane (QC) assignment, and QC scheduling for (un)loading containers. Note that stowage planning is the only function not solely controlled by the terminal operator but received significant input from the captain of the vessel. Storage yard operations include stacking and retrieving inbound, outbound, and transshipment containers from yard blocks by gantry cranes (GCs). Internal transport vehicles (ITVs) provide container transfer between the seaside and the storage yard. Landside operations consist in receiving or delivering containers by drayage trucks (DTs), entering the terminal through dedicated gates. There are three main seaside transfer processes in conventional marine container terminals (MCTs): a) vessel-to-yard (or import), b) yard-to-vessel (or export), c) and vessel-to-vessel (a.k.a. transshipment). These transfer operations are illustrated in Figures 2 and 3.

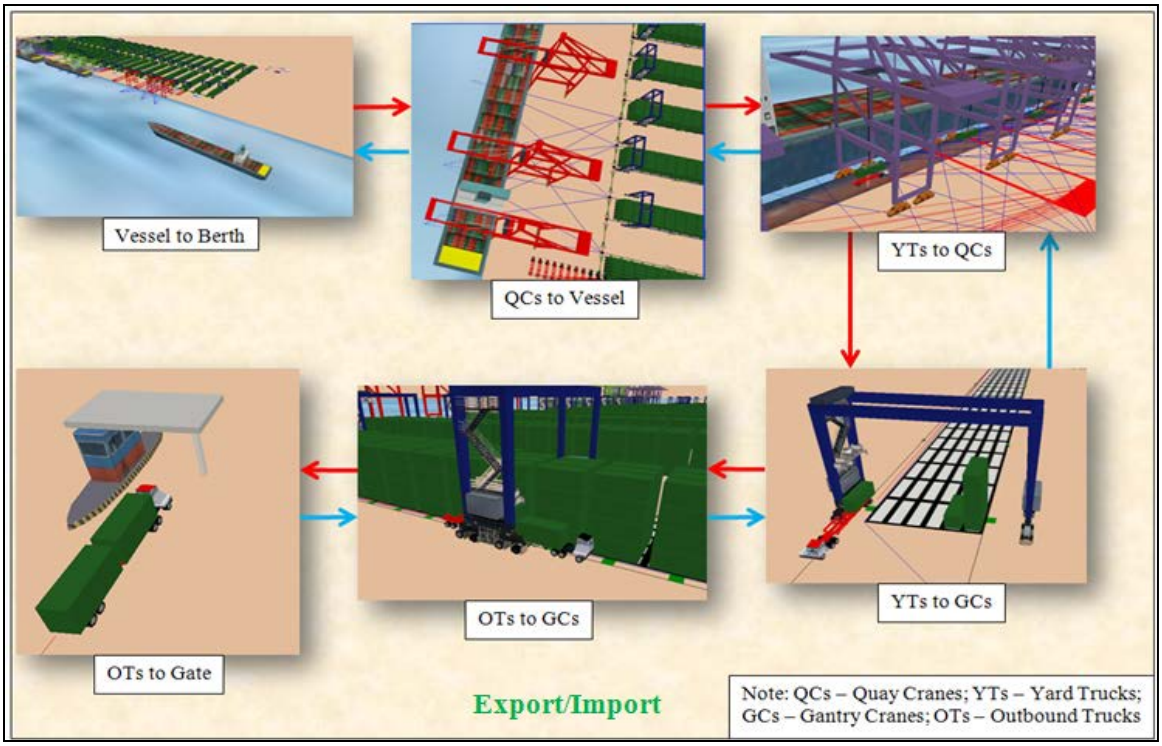


Figure 2. MCT Export/Import Operations

Conventional maritime terminals operate as follows: once a vessel has entered the port, it is berthed at its assigned berth, and once moored, ship-to-shore QCs start (un)loading containers. ITVs (yard trucks, straddle carriers, automated guided vehicles, automated lifting vehicles, etc.) transfer containers between the seaside and pre-assigned blocks of the storage yard, where GCs arrange them either parallel or perpendicular to the berth. Import containers are delivered to the port by vessels, while export containers are drayed to the port by DTs through the gates (usually at least 24 hours before the vessel calls at the port). Once a DT enters a terminal, it travels to the assigned blocks in the storage area, where a GC (un)loads a container. Smaller cranes (e.g., reachstackers, loaded/empty container handlers, etc.) also can be used for service of DTs. Transshipment occurs, when cargo, delivered by one vessel (usually called as mother

vessel), is moved to another vessel (usually called as feeder vessel). Transshipment containers can be transported from vessel to vessel with or without temporary storage at the storage yard.

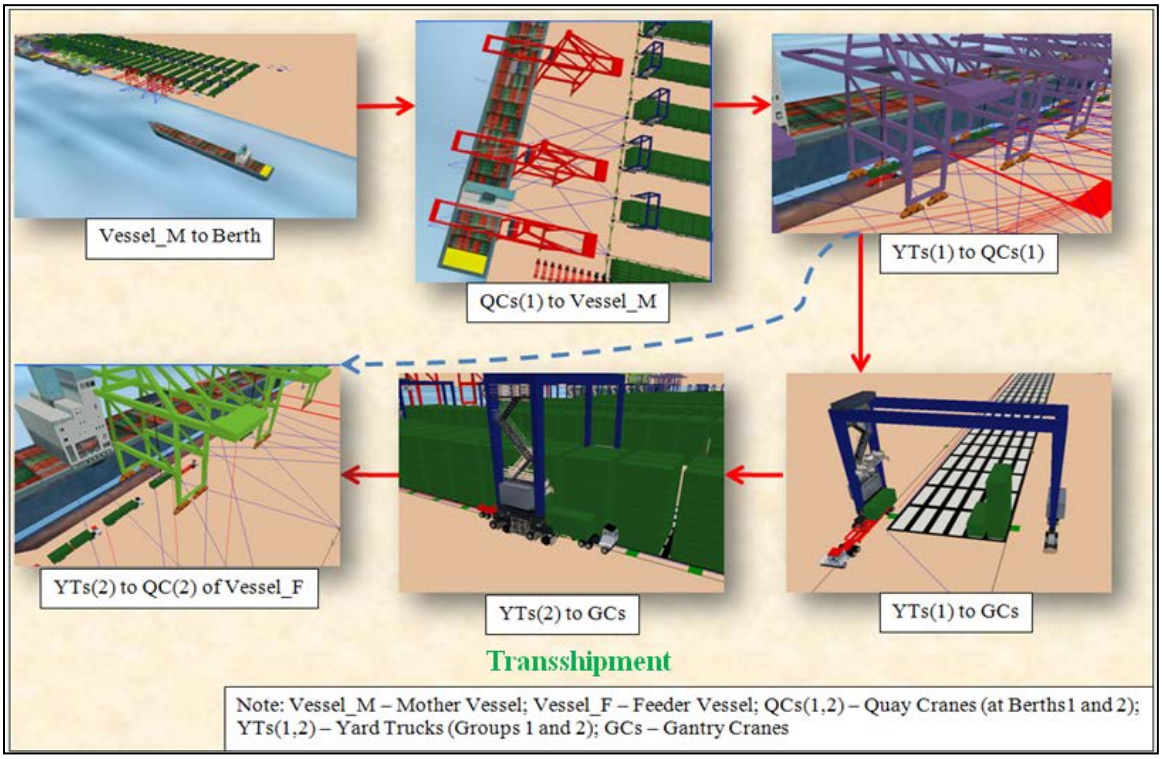


Figure 3. MCT Transshipment Operations

Realizing efficient operations at conventional MCTs remains a difficult task (most operations formulated as mathematical programing models belong to the NP class). Handling equipment and containers should be properly allocated for seaside, landside and storage areas. QCs should be assigned to particular berths, and their quantity is based on several factors (i.e., the total number of QCs available; the total number of vessels, assigned to each berth; the total number of containers to be handled for each vessel, etc.). Particular dispatching strategies of ITVs should be chosen in order to decrease or

eliminate idle time of QCs. Available GCs should also be properly allocated between yard blocks. If more than one GC serves a yard block, particular safety policies should be taken into account to avoid clashing. There are also traffic congestion issues for large MCTs due to longer travel distances by ITVs. The allocated equipment should be utilized in the most efficient manner (e.g., dual cycling of QCs and horizontal transportation units).

The main objective of this dissertation is to develop models and solution algorithms that will assist liner shipping companies and marine container terminal operators in improving efficiency of their operations.

Contributions

Contributions of the conducted work can be outlined as follows:

1) Assessing benefits of the floaterm concept

a. Estimated equipment and vessel service makespan savings, QC productivity, and the total construction and maintenance cost savings

b. Improving MCT resilience

2) A new berth scheduling policy for dedicated MCTs with excessive demand

a. A mixed integer non-linear mathematical program for modeling the policy

b. Memetic Algorithm for solving the program and estimating potential benefits from the adopted berthing policy

3) A new collaborative agreement between liner shipping companies and MCT operators

a. A mixed integer non-linear mathematical program for modeling the agreement

b. A novel approach for calculating the approximated bunker consumption value

c. Exact solution algorithm for the proposed model

d. Quantifying the potential benefits, yielded by the suggested collaborative mechanism

4) Defining a novel framework for modeling uncertainty in liner shipping

a. Description of the new methodology

b. Complexity and solution algorithm discussion

Structure of the Manuscript

The manuscript is organized as follows. The next chapter presents a literature review, mainly focusing on MCT seaside operations. The third chapter discusses application of the floaterm concept to improve productivity of MCTs under normal and disruptive operational conditions. The fourth chapter introduces a new berthing policy for dedicated MCTs with excessive demand. The fifth chapter overviews the literature, related to the tactical problems in liner shipping, describes the fleet deployment problem with variable sailing speed and port service times, and proposes the solution approach for that problem. The sixth chapter presents a new framework for modeling uncertainty in liner shipping. The last chapter provides conclusions and future research directions.

2. LITERATURE REVIEW

An extensive literature search was performed through various databases, containing journal publications, conference proceedings, and scientific manuscripts (i.e., Master Theses and Doctoral Dissertations). The following key words were used during the search: MCTs, container, seaside operations, port, handling equipment at container terminals, vessel, ITVs at seaports, and QCs. The search was stopped, when the overall number of studies reached 300 units. Then all articles were separated by various topics: 1) Berth allocation and scheduling, 2) Stowage planning, 3) QC assignment and scheduling, 4) Landside and seaside transport, 5) Storage and stacking, 6) Vulnerability and resiliency of seaports, and 7) Miscellaneous. This dissertation will mainly emphasize on seaside decision problems, as the bottleneck in MCT operations usually occurs at the seaside (Carlo, Vis, & Roddbergen, 2013; Golias, 2007). The total number of publications, dealing with seaside decision problems, comprised 159: berth allocation and scheduling (BSP) – 32%, QC assignment and scheduling (QCA&SP) – 26%, seaside transport decision problems (STDP) – 24%, and integrated seaside decision problems (ISDP) – 18%. The literature review, presented in this chapter, is solely focused on BSP. Additionally, the literature review on liner shipping operations was performed and findings will be outlined in chapter 5.

The main BSP objective is to assign vessels to berthing positions at MCT to be served during particular time periods, taking into account geometrical berth and vessel characteristics (i.e., the total length of the wharf vs. the overall length of vessels to be served, the minimum depth along the wharf vs. the maximum draft among all vessels to be served, etc.). Excellent BSP literature reviews were conducted is the past: Stahlbock

and Vos (2008), Theofanis, Boile, and Golias (2009), Bierwirth and Meisel (2010, 2015), and Carlo et al. (2013). A classification scheme of BSP papers will be similar to the ones, adopted by Bierwirth and Meisel (2010, 2015), and Carlo et al. (2013), with minor modifications. Conducted in the past studies will be described based on the following attributes: spatial, vessel arrivals, handling times, and performance measures (or objectives).

Based on the spatial attribute the reviewed BSPs will be differentiated as discrete, continuous, hybrid, and draft consideration (see Table 2). In the discrete BSP (DBSP), the wharf is subdivided in a certain number of berths (see Figure 4a-b). Only one vessel can be served at each berth at the time. As for the continuous BSP (CBSP), the wharf is limited only by its length and not partitioned in berths (see Figure 4c). In this case several vessels can be served as long as their overall length does not exceed the wharf's length. In the hybrid BSP (HBSP), the wharf is subdivided in a certain number of berths, but larger vessels can occupy more than one berth, while several smaller vessels can be served at one berth (see Figure 4d-f). An indented berthing layout, initially implemented at Ceres Container Terminal (the Netherlands) and described in details by Carlo et al. (2013), is classified as hybrid (see Figure 4f). There are some studies, considering the draft of vessels as an additional BSP constraint (see Figure 4g). Larger vessels with drafts, exceeding the maximum allowable draft, cannot be moored at particular berthing positions.

The vessel arrivals attribute separates BSPs in three types: static, dynamic, and controlled (see Table 2). In the static BSP (SBSP), all vessels have already arrived to the port, and the schedule should be developed based on particular objective(s). As for the

dynamic BSP (DBSP), approximate arrival times of vessels are known for a certain time horizon. In the last case (controlled vessel arrivals) the terminal operator negotiates vessel arrival times with a liner shipping company. The arrival times can be assigned as parameters (i.e., constant values) or as variables (i.e., set of upper and lower bounds, and probability distributions).

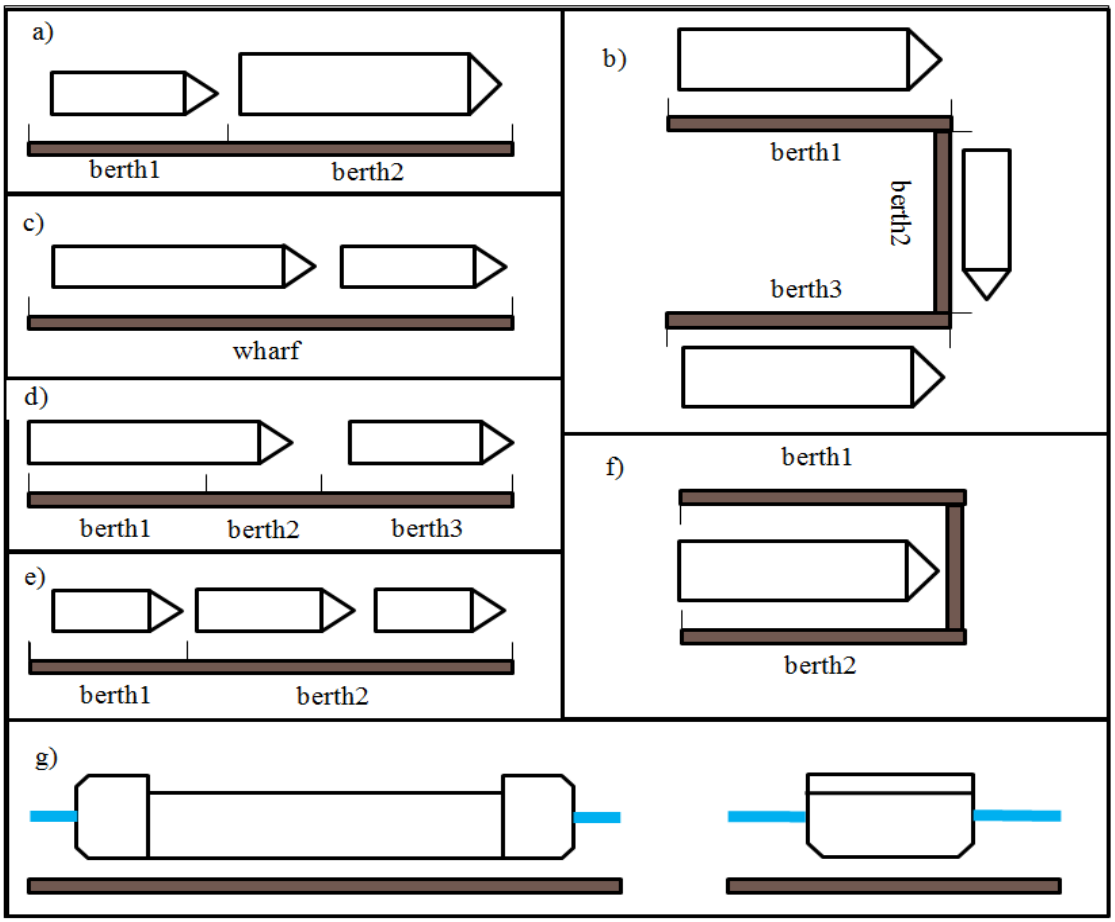


Figure 4. BSP Spatial Attribute

Similarly, the vessel handling times can be differentiated as fixed and variable (see Table 2). When the handling time is constant, it is assumed that the quantity of QCs,

assigned for the service of a vessel, does not change along with QC productivities over the considered time horizon. Variable handling times can be set in different ways: a) function of the berthing position (the preferred berthing position will result in the maximum QC productivity), b) function of handling volumes, c) function of assigned QCs to each vessel, and d) stochastic parameter. Constant arrival and handling times of vessels are very seldom. Assumption with variable arrival and handling times is more realistic and also allows capturing possible uncertainties.

Table 2
Description of the BSP Attributes

Attribute	*Description*
1) Spatial	
- D	discrete
- C	continuous
- H	hybrid
- Dr	vessels draft consideration
2) Vessel arrivals	
- S	static
- D	dynamic
- P	controlled
3) Handling times	
- C	constant
- V	variable
4) Performance measures	
Compl	completion time of all vessels service
Wait	waiting time of vessels
Hand	handling time of vessels
Late	late departures of vessels
Dev	deviation between actual and desired berthing positions
Fail	failing to provide a service request
Order	deviation between arrived vessels order and their service order
Fuel	fuel consumption of vessels
Other	different from ones, listed above
w	weighted coefficient

The last classification feature is a performance measure, which represents an objective function to be minimized. The list of performance measures is given in Table 2. If a mathematical model has an objective, different from ones, mentioned in the list, it will be assigned to the category “Other”. When a performance measure is maximized, it will have a negative coefficient. The most common objective of BSPs, revealed in the literature, is minimization of the total turnaround time of vessels (often presented as a sum of waiting and handling times for all vessels).

The reviewed papers will be classified according to the following structure: spatial attribute |vessel arrivals attribute |handling times attribute |performance measures attribute. For example, an abbreviation D&Dr|D|C|Σ(Wait+Hand)|BSP means a discrete dynamic BSP, taking into account the draft of vessels and assuming constant handling times, directed to minimize the total turnaround time of vessels. The list of notations for solution approaches, implemented by researches, is presented in Table 3.

Table 3
List of Notations for Solution Approaches

Solution Approach	*Notation*
Branch-and-Bound Algorithm	B&B
Branch-and-Cut Algorithm	B&C
Branch-and-Price Algorithm	B&P
Evolutionary Algorithm	EA
Greedy Randomized Adaptive Search Procedure	GRASP
Simulated Annealing	SA
Squeaky Wheel Optimization	SWO
Stochastic Beam Search	SBS
Tabu Search	TS
Variable Neighborhood Search	VNS

An overview of the BSP formulations is given in Table 4. More detailed description of collected studies is presented in sections below. These sections will be differentiated only based on the spatial attribute (DBSP – 57%, CDAP – 31%, and HBSP – 12%), since the majority of authors considered dynamic vessel arrivals with variable handling times (only a few papers presented SBSP formulation, as a supplement to DBSP formulation).

Discrete Berth Scheduling Problems (DBSPs)

Brown, Cormican, Lawphongpanich, and Widdis (1997) studied a BSP for the US Navy nuclear submarines. The authors proposed a linear integer formulation with the objective, directed to maximize the total benefit from less penalties due to berth shifts and failing to provide requested services. CPLEX was used to solve the problem. Computational experiments were conducted based on the data from the Naval Submarine Base in San Diego. Results indicated efficiency of the suggested methodology. Imai, Nishimura, and Paradimitriou (2001) presented static and dynamic BSP formulations. The objective in both cases minimized the total waiting and handling times of vessels. A Lagrangian relaxation based heuristic was proposed as the solution algorithm. Imai, Nishimura, and Paradimitriou (2003) considered a similar problem. The authors also introduced a vessel priority by assigning a weighted parameter, which was represented as a function of the cargo handling volume. An EA heuristic was applied to solve the problem. It was observed that the vessel service time was highly dependent on the weighted parameter, assigned to each category of vessels.

Hansen and Oguz (2003) presented mathematical formulations for static and dynamic BSPs. The objective of both models minimized the total vessel service time. The

authors reformulated the model, developed by Imai et al. (2001). CPLEX was applied to solve both problems. Numerical experiments, conducted based on a real-life data, indicated the necessity of a more efficient solution approach. Cordeau et al. (2005) suggested two DDBSP formulations. The first one was similar to Imai et al. (2001), while the second presented DDBSP as a Multi-Depot Vehicle Routing Problem with Time Windows (MDVRPTW). The objectives of both models minimized the total weighted vessel service time. Small size instances were solved optimally with CPLEX. For large size problems a TS heuristic was developed. Computational examples were performed based on the data, collected from the Port of Gioia Tauro (Italy). Results demonstrated the efficiency of the proposed methodology.

Li, Tang, and Liu (2005) addressed DSBSP at raw material docks. The considered terminal had various berth structures. The objective of MIP aimed to minimize the total vessel service tardiness. The authors derived a lower bound using a Largangian relaxation and applied the B&B algorithm to solve the problem. Boile, Theofanis, and Golias (2006) investigated DDBSP with service priorities. A vessel priority was assigned by a specific weight. The objective minimized the total weighted vessel service time. A heuristic was developed to solve the problem. Numerical experiments indicated that the proposed solution approach was efficient for small size instances. Zhou, Wang, Kang, and Jia (2006) formulated DDBSP with variable service priorities at MCT. The objective minimized the total vessel waiting times. An EA based heuristic was proposed as the solution algorithm. Computational examples showed that the presented model substantially reduced vessel waiting times. The developed algorithm obtained good solutions in a reasonable computational time.

Imai, Zhang, Nishimura, and Paradimitriou (2007) studied a bi-objective DDBSP. The first objective of the model minimized the total vessel late departures, while the second one aimed to minimize the total vessel service time. A Lagrangian relaxation and an EA based heuristics were used to solve the problem. Numerical experiments demonstrated that the EA heuristic obtained better quality solutions. Golias (2007) presented models and solutions algorithms for various BSPs in his dissertation, capturing the MCT technical and operational characteristics. Discrete and continuous berthing layouts were considered. Objectives were directed to minimize the total cost from delayed departures/berthing, the total handling and waiting costs, maximize the total premium from timely and early departures, etc. Various solution heuristics were applied to solve different problems (EA, SWO, VNS, etc.). Necessary conclusions and the scope of future research were provided. Golias, Boile, and Theofanis (2007) formulated DDBSP as a linear mixed integer problem, taking into account time window service deadlines. The authors suggested several changes in the model, presented by Imai et al. (2001, 2003). The objective minimized the total penalties due to late vessel departures and maximized the total benefits due to timely and early vessel departures. CPLEX was used to solve the problem. Numerical examples were conducted for small size instances.

Hansen, Oguz, and Mladenovic (2008) formulated DDBSP, minimizing the total cost, which included waiting time cost, handling time cost, and penalties due to late vessel departures. The authors developed a VNS heuristic. Computational experiments showed the efficiency of the suggested solution approach. VNS outperformed Multi-Start Heuristic (MS), EA, and Memetic Search Algorithm (MA). Imai, Nishimura, and Paradimitriou (2008) proposed static and dynamic DBSP formulations for a multi-user

terminal. Vessels with expected waiting times, exceeding a set limit, were assigned for service at the external terminal. The objective minimized the total vessel service time at both external and multi-user terminals. The authors presented an EA based heuristic to solve the problem. Numerical examples demonstrated the robustness of the algorithm and efficiency of a new berthing policy for a terminal operator especially during peak hours.

Golias, Boile, and Theofanis (2009) studied DDBSP at container terminals, where the vessel service was differentiated based on priority agreements. The objective function was directed to minimize the total vessel service time. An EA based heuristic was developed to solve the problem. Golias, Boile, Theofanis, and Efstathiou (2010) presented a new DDBSP formulation, taking into account vessels' fuel consumption. The objective minimized the total vessel service time, delayed departures, fuel consumption, and emissions productions. The authors applied an EA to solve the problem. Golias, Boile, and Theofanis (2010a) introduced a lambda-optimal based heuristic for DDBSP. The objective minimized the total weighted service time of vessels. An EA was used to check the performance of the suggested heuristic for medium and large size problems. It was observed that the lambda-optimal based heuristic showed an adequate performance within acceptable computational time.

Golias, Boile, and Theofanis (2010b) studied DDBSP, taking into account the major terminal operator goals. The objective minimized the total cost from vessels' waiting and handling times, late departures, deviation from the agreed vessel productivity, and to maximize the premiums from early and timely departures. CPLEX was used for various problem instances. The procedure was stopped if the solution was not found after 2 hours. Golias and Haralambides (2010) formulated DDBSP for MCT,

where the terminal operator had various contractual agreements with liner shipping companies (i.e., different cost functions). The objective minimized the total cost of vessels' waiting time and late departures, and maximized the total premiums from early departures. The authors applied an EA to solve the problem. Computational experiments were performed for various cost policies.

Saharidis, Golias, Boile, Theofanis, and Ierapetriou (2010) considered DDBSP at MCT with two hierarchical levels for vessels (preferential and non-preferential). The objective aimed to minimize the total vessel service time. The authors presented a heuristic, called k-th best algorithm, to solve the problem. Numerical examples showed that the proposed algorithm was efficient and provided (near)optimal solutions in acceptable computational time. Arango, Cortes, Munuzuri, and Onieva (2011) studied DDBSP at a container terminal of the Port of Seville (Spain). The objective minimized the total vessel turnaround time. An EA and the Arena simulation software were applied to solve the problem. An optimization module was used to generate a vessel to berth assignment and send the information to the simulation module, which performed the vessel handling. Computational experiments confirmed that the proposed methodology could significantly improve the existing berth management strategy.

Buhrkal, Zuglian, Ropke, Larsen, and Lusby (2011) reviewed several berth allocation models: 1) Imai et al. (2001), minimizing the total vessel waiting and handling times, 2) a Heterogeneous Vehicle Routing Problem with Time Windows formulation (HVRPTW), minimizing the total vessel weighted service time, 3) an improved HVRPTW problem, minimizing the total vessel weighted service time, and 4) a generalized set partitioning problem, minimizing the total vessel service time. CPLEX

was used to solve all models. It was observed that a generalized set partitioning model outperformed all other considered models. De Oliveira, Mauri, and Lorena (2012) formulated DDBSP, aiming to minimize the total weighted vessel service time. The authors developed a Clustering Search (CS) heuristic to solve the problem. Numerical experiments were conducted based the data, collected from the Port of Gioia Tauro (Italy). It was found that the CS outperformed other solution approaches (i.e., TS, column generation, and SA). Lalla-Ruiz, Melian-Batista, and Moreno-Vega (2012) studied DDBSP, directed to minimize the total service time of vessels. The authors presented a heuristic, based on the TS and the Path Relinking (TSPR). The proposed solution approach was compared with a Generalized Set Partitioning Problem (GSPP). Computational examples demonstrated that TSPR outperformed GSPP for small and large problem sizes.

Sun (2012) studied the following BSPs in his dissertation: multiple BSP (MBSP), integrated BSP & QCA&SP (BAQCSP), and MBSP & QCA&SP (MBAQCSP). Various types of berthing layouts were discussed: discrete, continuous, and semi-continuous (or hybrid). Based on vessel arrival times BSPs were classified into static and dynamic. The objectives of considered problems were directed to minimize the total vessel turnaround time and penalties due to late vessel departures. The MBSP was solved by the B&P algorithm. The author developed a heuristic based on EA and TS to solve BAQCSP and MBAQCSP. Numerical experiments were performed based on randomly generated test problems. Results showed efficiency of suggested methodologies and solution approaches. Xu, Li, and Leung (2012) presented formulations for static and dynamic BSPs. The BSP was modeled as a parallel-machine scheduling problem, minimizing the

total weighted completion time of vessels. The authors presented heuristic algorithms to solve dynamic and static problems. Cubillos et al. (2013) proposed a multi-agent based approach for DDBSP. The system architecture included the interface layer (Ship Agent and Berth Agent) and the planning layer (Bert Request Agent, Dock Agent, Berth Planner Agent, and Central Agent). The objective maximized the vessel throughput and the berth utilization. The multi-agent architecture was created using the java environment. The insertion algorithm was employed to count for new vessels joining to an existing berth sequence.

Golias, Portal, Konur, Kaisar, and Kolomvos (2013) considered DDBSP at MCT, where arrival and handling times of vessels were assigned with upper and lower bounds. The objective of a bi-level mixed integer model minimized the average total service time of vessels and the total range of service times. The authors developed an EA heuristic to solve a non-convex problem. Numerical experiments were conducted for 48 problem instances. Karafa, Golias, Ivey, Saharidis, and Leonardos (2013) investigated DDBSP with stochastic handling times of vessels. The problem was bi-objective. The first objective aimed to minimize the expected total service time of vessels, while the second objective minimized the service start and finish time risks for all vessels. An EA based heuristic was applied to solve the problem. Computational experiments demonstrated that better solutions were obtained for the cases with stochastic vessel handling times, than for the cases with expected handling time values.

Continuous Berth Scheduling Problems (CBSPs)

Moon and Kim (2000) studied CDBSP at MCT, aiming to minimize the total operational cost, associated with deviations from the desired vessel berthing positions and

penalties due to late vessel departures. The authors developed a heuristic to solve the problem. Numerical experiments indicated that the algorithm obtained results close to the ones, provided by the optimization solver. Guan, Xiao, Cheung, and Li (2002) formulated a multiprocessor task scheduling problem as CSBSP, where QCs were represented as processors, and vessels were modeled as jobs. The objective of the problem was directed to minimize the total weighted vessel service time. The authors applied a heuristic to solve the problem. A set of lemmas and the worst-case analysis were presented as well. Kim and Moon (2003) proposed a mixed integer linear CDBSP, minimizing the cost, associated with deviations of the desired vessel berthing positions and penalties due to late vessel departures. The authors developed a SA based algorithm to solve the problem and compared results with the ones, obtained by the LINGO solver. Computational examples showed the robustness of the proposed methodology and the solution approach.

Dai, Lin, Moorthy, and Teo (2004) investigated static and dynamic CBSPs. The first objective was directed to minimize the total delays of vessels, while the second one aimed to maximize the berth utilization. The authors developed a SA based heuristic to solve CSBSP. CDBSP with various vessel arrival scenarios was solved using simulation. It was observed that the most of vessels were assigned to the desired berthing positions in the dynamic case. More efficient algorithm would be required for the static case to reduce the difference with lower bound. Guan and Cheung (2005) formulated CDBSP, aiming to minimize the total weighted service time of vessels. The authors presented a composite heuristic, which combined a tree search procedure and a pair-wise exchange heuristic. Imai, Sun, Nishimura, and Paradimitriou (2005) suggested a mathematical model for CDBSP, directed to minimize the total vessel service time. The time arrivals of vessels

followed the exponential distribution. The handling times were dependent on the vessel berthing positions. The authors developed a heuristic to solve the problem. Numerical experiments indicated that continuous berthing layout would be more effective as compared to the discrete one, especially in cases when there were fewer berths at MCT.

Wang and Lim (2007) presented a SBS heuristic for CDBSP. The objective aimed to minimize the total operational cost, associated with possible unallocation, and penalties due to deviations from the desirable vessel berthing positions and late departures. Computational examples were presented using real-life data, provided by the Port of Singapore. Results demonstrated that SBS outperformed SA, developed by Dai et al. (2004). Lee and Chen (2009) formulated CDBSP, directed to maximize the berth utility index, presented as a function of vessel waiting time, priority, shifting status, and preferred berthing position. The authors applied a VNS to solve the problem. Numerical experiments were performed based on the data, collected from the Port of Kaohsiung (Taiwan). Results showed the robustness of the suggested algorithm for large instance problems. Du, Chen, Quan, Long, and Fung (2011) studied CDBSP, minimizing the total vessel fuel consumption and late departures. A heuristic was developed to solve the problem. Computational examples indicated that the strategy of introducing variable vessel arrivals led to lower emissions, comparing to the constant vessel arrival case.

Javanshir and Ganji (2010) investigated CDBSP at MCT, minimizing the total vessel service time. Vessel handling times varied depending on the berthing positions. The authors used the LINGO package to solve the problem. Numerical experiments indicated that adequate locations of container storage areas and automation of handling processes could significantly improve the terminal productivity. Lee, Chen, and Cao

(2010) developed GRASP to solve CDBSP. The objective minimized the total weighted vessel turnaround time. It was observed that the proposed heuristic obtained high quality solutions within acceptable computational time. Silva, Novaes, and Coelho (2011) applied an EA based heuristic to solve CDBSP. The objective was directed to minimize the total berth allocation cost, including waiting and handling times of vessels, and the berth utilization. Computational experiments were conducted based on the data, collected from the Itajai Port (Brazil). Results showed the efficiency of the suggested methodology and the solution approach. Xu, Chen, and Quan (2011) formulated CDBSP, capturing uncertainties in vessel arrivals and handling times. The objective minimized the total late vessel departures and maximized the length of buffer time. The buffer time after the vessel service completion time provided an additional room in cases of uncertain delays. The authors developed the Robust Berth Scheduling Algorithm (RBSA), which was based on SA and B&B. Computational experiments indicated that the value of weighting parameter in the objective significantly affected performance of the suggested heuristic.

Emde and Boysen (2012) studied CDBSP at MCT, aiming to minimize the total vessel waiting time and the number of delayed containers. The authors presented a SA based heuristic to solve the problem. Numerical examples demonstrated that the proposed solution approach was able to obtain (near)optimal solutions in a reasonable computational time. Zhen and Chang (2012) formulated CDBSP, taking into account uncertainties of vessel arrivals and handling times. The first objective minimized the total operational cost, while the second one maximized the robustness of schedule. The authors presented a heuristic to solve the problem. The suggested methodology and the solution algorithm were found to be efficient for large size problems. Sheikholeslami, Itatim, and

Kobari (2013) investigated CDBSP, considering tidal constraints in the access channel. The objective minimized the total waiting and handling times for vessels. The weighted coefficients were assigned to each vessel based on its size and voyage type. An EA based heuristic was developed to solve the problem. Computational experiments were performed based on the operational data, collected from the Sharid Rajaee Port Complex in Iran. Results indicated robustness of the algorithm for small size problems.

Hybrid Berth Scheduling Problems (HBSPs)

Nishimura, Imai, and Paradimitriou (2001) studied HDBSP at MCT, aiming to minimize the total vessel service time. Two heuristics, based on the Lagrangian relaxation and EA, were presented to solve the problem. Numerical experiments were performed based on the data, provided by the Port of Kobe (Japan). The EA heuristic was found to be more efficient. Moorthy and Teo (2006) formulated a bi-objective HDBSP. The first objective minimized the total vessel delays, while the second one aimed to minimize the connectivity cost (which was dependent on the vessel berthing position). Delays were assumed to follow the normal distribution. The authors used simulation and the greedy neighborhood search to solve the problem. Computational examples demonstrated robustness of the suggested methodology and the solution approach.

Imai, Sun, Nishimura, and Paradimitriou (2007) considered HDBSP at a multi-user container terminal with indented berths for a fast handling of mega-containerships. The objective minimized the total vessel service time. An EA based heuristic was developed to solve the problem. It was found that the handling time for mega-containerships was shorter at the indented berth terminal, but the total service time didn’t vary as compared to the conventional berth terminal. Cheong, Tan, Liu, and Lin (2008)

studied a multi-objective HDBSP, aiming to minimize the makespan, waiting time of vessels, and degree of deviation from a predetermined priority schedule. The authors used the Pareto optimality concept and the Multi-Objective EA (MOEA) to solve the problem. Numerical experiments indicated that particular features of the algorithm (i.e., local search, solution decoding schemes, and the optimal berth insertion) affected significantly its performance. Cheong and Tan (2008) considered a similar problem, minimizing the total vessel service time and total delays due to late vessel departures. A Multi-Objective Multi-Colony Ant Algorithm (MOMCAA) was suggested as a solution approach. The algorithm was found to be efficient to find the (near)optimal solutions within reasonable computational time.

Imai, Nishimura, and Paradimitriou (2013) investigated HDBSP at MCT, serving mega-containerships. Three terminal layouts were presented: conventional (containers are handled from one side of a vessel at the assigned berth), channel (containers are handled from two sides of a vessel along the channel), and indented (a vessel is served at an indented berth). Various vessels sizes were considered. The objective minimized the total vessel service time. The authors applied an EA based heuristic to solve the problem. It was found that channel terminals were more efficient than conventional berth terminals and indented berth terminals, since the total service time of vessels including mega-containerships was the shortest in the majority of cases.

Table 4
Overview of BSP Formulations

Authors (year)\Attribute	*Spatial*	*Vessel arrivals*	*Handling times*	*Objective(s)*
Brown et al. (1997)	D	D	C	Σ(Fail + Dev)
Moon & Kim (2000)	C	D	C	$\Sigma[w_1(\text{Dev}) + w_2(\text{Late})]$
Imai, Nishimura, & Paradimitriou (2001)	D	S&D	V	Σ(Wait + Hand)
Nishimura, Imai, & Paradimitriou (2001)	H&Dr	D	V	Σ(Wait + Hand)
Guan et al. (2002)	C	S	C	max[w(Compl)]
Hansen & Oguz (2003)	D	S&D	V	Σ(Wait + Hand)
Imai, Nishimura, & Paradimitriou (2003)	D	D	V	Σw(Wait + Hand)
Kim & Moon (2003)	C	D	C	$\Sigma[w_1(\text{Dev}) + w_2(\text{Late})]$
Dai et al. (2004)	C	S&D	C	Σ(Dev) & Σ(Late)
Cordeau et al. (2005)	D	D	V	Σw(Wait + Hand)
Guan & Cheung (2005)	C	D	C	Σw(Wait + Hand)
Imai et al. (2005)	C	D	V	Σ(Wait + Hand)
Li, Tang, & Liu (2005)	D&Dr	S	V	Σ(Late)
Boile, Theofanis, & Golias (2006)	D	D	V	Σw(Wait + Hand)
Moorthy & Teo (2006)	H	D	V	Σ(Dev + Late)
Zhou et al. (2006)	D&Dr	D	V	Σw(Wait)
Imai et al. (2007a)	D	D	V	Σw(Late) & Σ(Wait + Hand)
Imai et al. (2007b)	H	D	V	Σ(Wait + Hand)
Golias (2007)	D&C	D	V	$\Sigma[w_1(\text{Wait}) + w_2(\text{Hand}) + w_3(\text{Late})] + w_4(\text{Other})]$
Golias, Boile, & Theofanis (2007)	D	D	V	$\Sigma[w_1(\text{Late}) + w_2(\text{Other})]$
Wang & Lim (2007)	C	D	C	$\Sigma[w_1(\text{Fail}) + w_2(\text{Dev}) + w_3(\text{Late})]$
Cheong et al. (2008)	H&Dr	D	V	max(Compl) & Σ(Wait) & Σ(Order)
Cheong & Tan (2008)	H&Dr	D	V	Σ(Wait + Hand) & Σ(Late)
Hansen, Oguz, & Mladenovic (2008)	D	D	V	$\Sigma[w_1(\text{Wait}) + w_2(\text{Hand}) + w_3(\text{Late})]$
Imai, Nishimura, & Paradimitriou (2008)	D	S&D	V	Σ(Wait + Hand)
Golias, Boile, & Theofanis (2009)	D	D	V	Σ(Wait + Hand)
Lee & Chen (2009)	C	D	V	Other
Golias et al. (2010)	D	D	V	Σ(Wait + Hand + Late + Fuel)
Golias, Boile, & Theofanis (2010a)	D	D	V	Σw(Wait + Hand)
Golias, Boile, & Theofanis (2010b)	D	D	V	$\Sigma[w_1(\text{Wait}) + w_2(\text{Hand}) + w_3(\text{Late}) + w_4(\text{Other})]$

Table 4
Overview of BSP Formulations (continued)

Authors (year)\Attribute	*Spatial*	*Vessel arrivals*	*Handling times*	*Objective(s)*
Golias & Haralambides (2010)	D	D	V	$\Sigma[w_1(\text{Wait}) + w_2(\text{Late}) + w_3(\text{Other})]$
Javanshir & Ganji (2010)	C	D	V	Σ(Wait + Hand)
Lee, Chen, & Cao (2010)	D	D	V	Σw(Wait + Hand)
Saharidis et al. (2010)	D	D	V	Σ(Wait + Hand)
Arango et al. (2011)	D	D	V	Σ(Wait + Hand)
Buhrkal et al. (2011)	D	D	V	Σ(Wait + Hand)
Du et al. (2011)	C	S&D	C	Σ(Late + Fuel)
Silva, Novaes, & Coelho (2011)	C&Dr	D	V	$\Sigma[w_1(\text{Wait}) + w_2(\text{Hand}) + w_3(\text{Other})]$
Xu, Chen, & Quan (2011)	C	D	V	Σw(Late) + Other
De Oliveira, Mauri, & Lorena (2012)	D	D	V	Σw(Wait + Hand)
Emde & Boysen (2012)	C	D	V	Σw(Wait) + Σ(Late)
Lalla-Ruiz, Melian-Batista, & Moreno-Vega (2012)	D	D	V	Σ(Wait + Hand)
Sun (2012)	D&Dr	S&D	V	Σ(Wait + Hand + Late)
Xu, Li, & Leung (2012)	D&Dr	S&D	V	Σw(Wait + Hand)
Zhen & Chang (2012)	D	D	V	$\Sigma[w_1(\text{Late}) + w_2(\text{Dev})]$ + Other
Cubillos et al. (2013)	D	D	V	Other
Golias et al. (2013)	D	D	V	Σ(Wait + Hand) + Other
Imai, Nishimura, & Paradimitriou (2013)	H	D	V	Σ(Wait + Hand)
Karafa et al. (2013)	D	D	V	Σ(Wait + Hand) + Other
Sheikholeslami, Itatim, & Kobari (2013)	C&Dr	D	V	Σw(Wait + Hand)

Literature Review Summary

As a result of conducted literature review the following gaps in the state of the art and current practices along with future research directions can be outlined:

a) The majority of authors investigated DBSPs (around 57% of all BSP papers). However, a continuous berthing layout is more efficient and allows higher berth utilization (Carlo et al., 2013). Despite the fact that CBSPs are more difficult to solve

than DBSPs, researches must focus on development of new mathematical models and heuristic algorithms for MCTs with a continuous berthing layout;

b) Only a few studies covered HBSPs (around 12% of all BSP papers). Imai et al. (2007b) indicated that vessel handling times at MCTs with an indented berthing layout (see Figure 4) are shorter than at terminals with a conventional berthing layout. Another research, conducted by Imai et al. (2013), indicated that the channel berthing layout (when vessels are handled from both sides along the channel, see Figure 5) provided faster service of mega-containerships as compared to traditional and indented berthing layouts. Since the hybrid berthing layout is more efficient, it should be investigated more in depth.

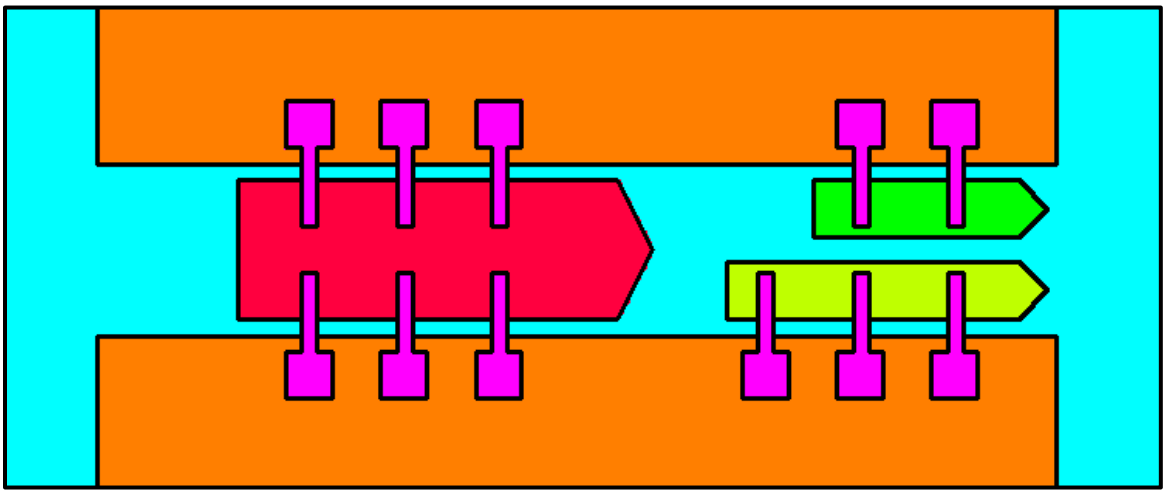


Figure 5. Channel Berthing Layout

c) New container handling systems should be paid more attention. Kim, Phan, and Woo (2012) presented various contemporary handling equipment types: linear motor conveyance system (LMCS), automated storage and retrieval system (AR/RS), overhead grid rail (GRAIL), speedport, SuperDock, AUTOCON, etc. The authors indicated that

those handling systems could improve operations at both seaside and landside. However, the installation of such handling equipment required a significant construction cost and could be economically infeasible.

d) Only few studies were dedicated to modeling various types of agreements between liner shipping companies and/or terminal operators. A collaborative agreement between liner shipping companies called “alliance”. The first liner shipping alliance appeared in 1990. By 1995 there were four major liner shipping alliances: Global Alliance, Grand Alliance, Maersk/Sea-Land, and Tricon (Cariou, 2002). Price rates for moving a particular cargo at the given route are established at Conferences. An alliance agreement may allow one liner shipping company moving cargo via another liner shipping company, which is a part of the alliance and provides more frequent service at the given route (Ararwal, 2007). Contractual agreements between terminal operators and liner shipping companies were evaluated by Golias (2007) and Golias and Haralambides (2010). Various forms of agreements have to be studied more in depth, as they may increase the terminal productivity without substantial investments.

e) An increasing size of vessels and the terminal congestion enforce a terminal operator to start thinking about new ways of container handling. Nam and Lee (2012) and Shin and Lee (2012) discussed a mobile harbor system, represented as a floating platform with on-board QC. The mobile harbor allows handling vessels in the sea. Liftech, Inc. and Ashar introduced a floaterm concept for improving seaside operations at MCTs (Ashar, 2013; Lifterch, Inc., 2007). The main difference between a conventional MCT and the one, which applies the floaterm concept, is that in the latter case floating QCs, located on the crane barge, are employed to handle containers that are either stored in the

floating storage yard or moved to the feeder vessels. Founders of the floaterm concept indicated that it would decrease the size of marshaling yard, mitigate or even eliminate terminal congestion issues, reduce the amount of required equipment, and decrease the turnaround time of vessels. Nevertheless, there are no mathematical/simulation models, quantifying potential benefits of this concept.

f) Bierwirth and Meisel (2015) underlined that the majority of researchers used stochastic search algorithms (e.g., Evolutionary Algorithms) for solving BSPs. The future research may focus on the development of additional local search heuristics, directed to improve objective function values and convergence patterns of the solution algorithms.

g) Only a few papers considered uncertainty in vessel arrivals, when solving BSP (Bierwirth & Meisel, 2015). Taking into account increasing number of vessels, arriving "off-schedule", it is necessary to provide a robust berth scheduling, which will allow MCT operators mitigate effects of possible uncertainties.

3. EVALUATION OF THE FLOATERM CONCEPT AT MARINE CONTAINER TERMINALS VIA SIMULATION

Introduction

As it was mentioned earlier, the amount of cargo, transported by vessels, substantially increased over the last 30 years. To meet the growing demand terminals operators have to increase productivity of their MCTs. To improve performance of MCTs by increasing quayside capacity with minimal capital investment a new concept (named floaterm) was proposed in early 2000 (Ashar, 2013; Lifterch, Inc., 2007). The floaterm concept includes two-sided operations (when a vessel is moored between the terminal berth and the crane barge as shown in Figure 6A) and midstream operations (when a vessel is moored to the crane barge in the sea as shown in Figure 6B). The floaterm concept was originally applied at the Ceres Terminal (Amsterdam, the Netherlands) in 2002 with throughput increasing by 24.6% from 2000 to 2005 (Pielage, Rijsenbrij, Van den Bosch, Ligteringen, & Van Beemen, 2008). No information was made available as to the role that the floaterm concept played in this increase. According to Liftech, Inc. (2007) and Ashar (2013) though the floaterm concept could significantly improve performance of seaports, decrease the size of the storage yard, reduce the number of handling equipment, reduce congestion, etc. An extensive literature search indicated that no computational study exists (to date), describing and modeling the impact of the floaterm concept on MCT operations. In this dissertation simulation will be used to compare operations (under normal and disruptive conditions) of a conventional MCT to a terminal with the floaterm concept and quantify (any) productivity gains, that may be realized by the latter.

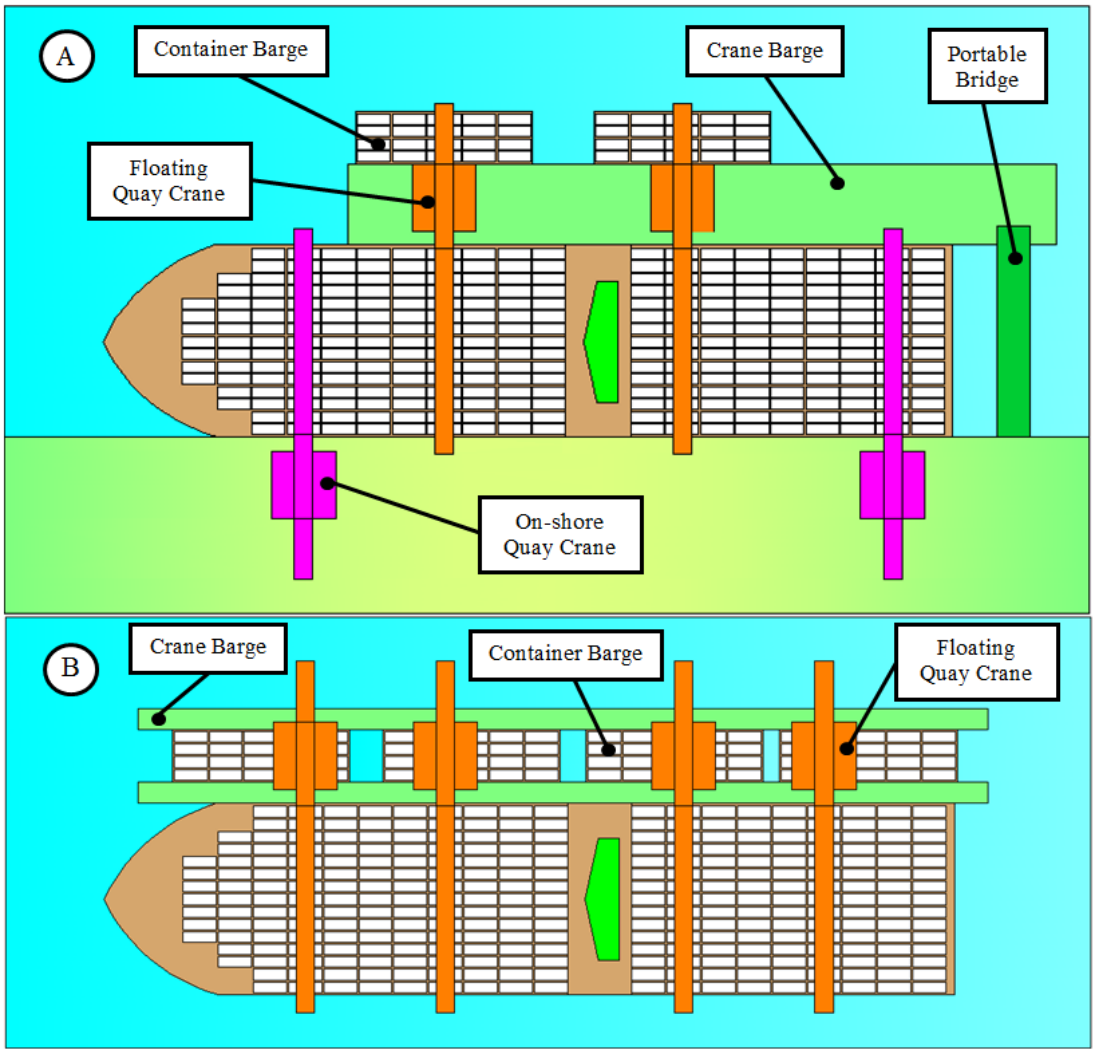


Figure 6. Two-Sided and Midstream Applications of the Floaterm Concept

Model Description

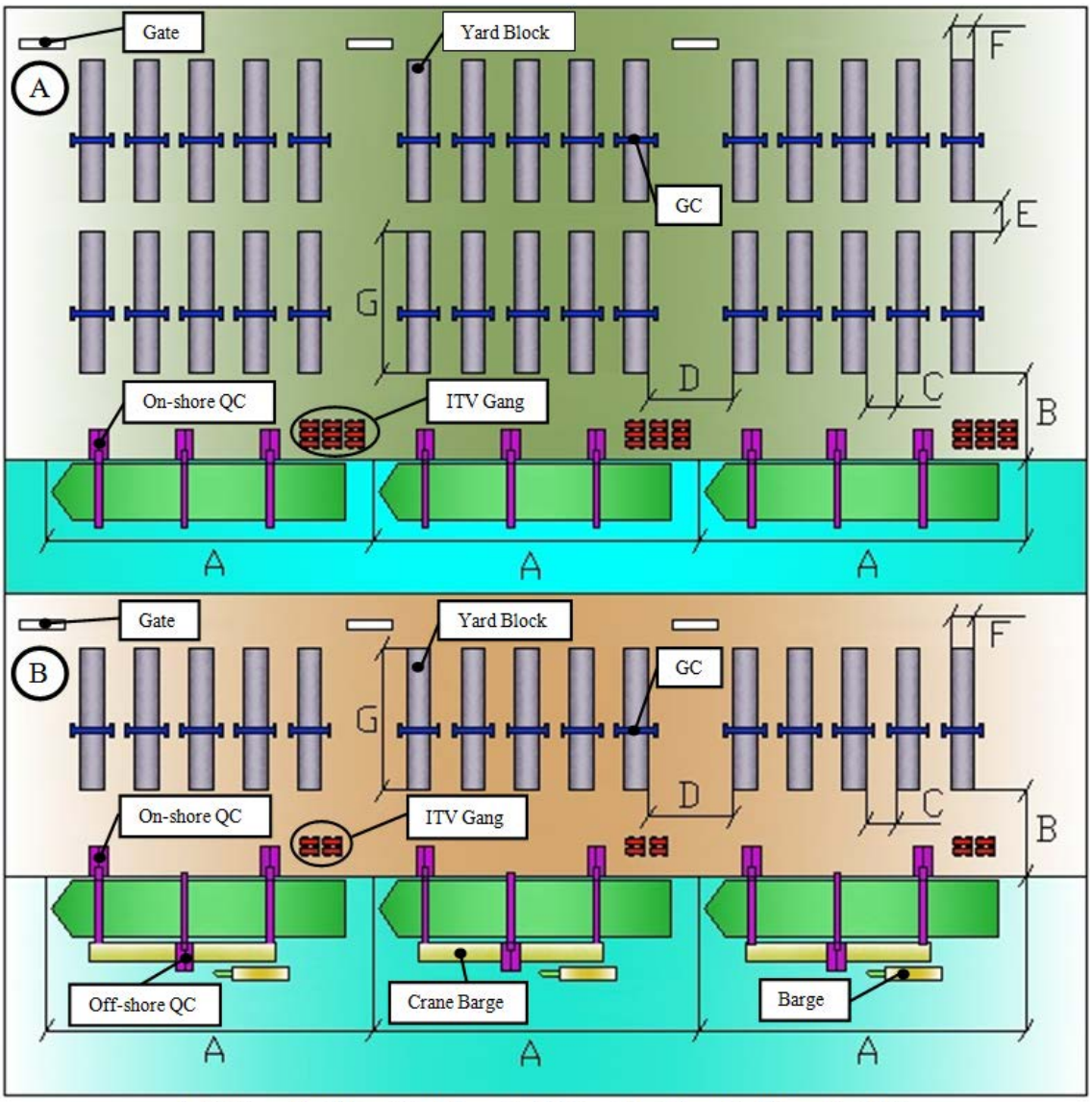
As revealed by the literature review, simulation is widely used for what-if scenario analysis and comparison of various resource assignment policies at MCTs. The scope of the past research, related to the floaterm concept, included theoretical discussions of its advantages (Ashar, 2013; Liftech, Inc., 2007), technical feasibility of the floating QCs application (Pielage et al., 2008), analysis of changes in the stowage planning (Pielage et al., 2008), economical and operational feasibility of the floaterm

concept (Pielage et al., 2008). The main objective of this study is to conduct a detailed comparative analysis of the conventional and floaterm terminal types using simulation modeling under normal and disruptive conditions. In this section two developed simulation models will be presented: one for a conventional and one for a floaterm MCT (from now on referred to as CMT and FMT respectively), using the FlexSim simulation software package (FlexSim, 2014), and estimate potential benefits of the latter terminal configuration. This section will describe in details the modeling assumptions of the quayside, yard, and landside operations for both terminals, including terminal layout, container types, handling equipment assignment, and characteristics of disruptive events.

Terminal and vessel characteristics. Both CMT and FMT are assumed to have 3 berths. The length of each berth is equal to 380m, which allows mooring of Neo-Panamax vessels. The width of the apron area, connecting the quayside and the storage yard, covers 90m. The main geometric characteristics of CMT and FMT are presented in Figure 7A and 7B respectively. Note that the terminal layout and dimensions for both CMT and FMT were based on information found in the available literature (Petering, 2009; Petering & Murty, 2008; Petering, Wu, Li, Goh, & Souza, 2009, etc.). Container flow is illustrated in Figure 8. At CMT three QCs are located on the quayside at each berth and handle all containers from each vessel.

At FMT two QCs are located on the quayside at each berth and only handle export and import containers, while one QC (at each berth), located on the crane barge, handles transshipment containers from/to the feeder barges (Dulebenets, Golias, & Heaslet, 2013). During disruptive events QCs on crane barges are also allowed to handle part of the import container demand. The capacity of each barge was assumed to be 200

TEUs. Once the barge is fully loaded, it is towed to the assigned feeder vessel by push boats. Setup time at the quayside is assumed to be 10 min (5 min for mooring 5 min for detaching). Setup time for the feeder barge (mooring to the crane barge and detaching from the crane barge) was assumed to be 10 min and can be modified in the model as needed.



A=380m; B=90m; C=15m; D=235m; E=30m; F=17m; G=146m;

Figure 7. Terminal Layouts: A-CMT, B-FMT

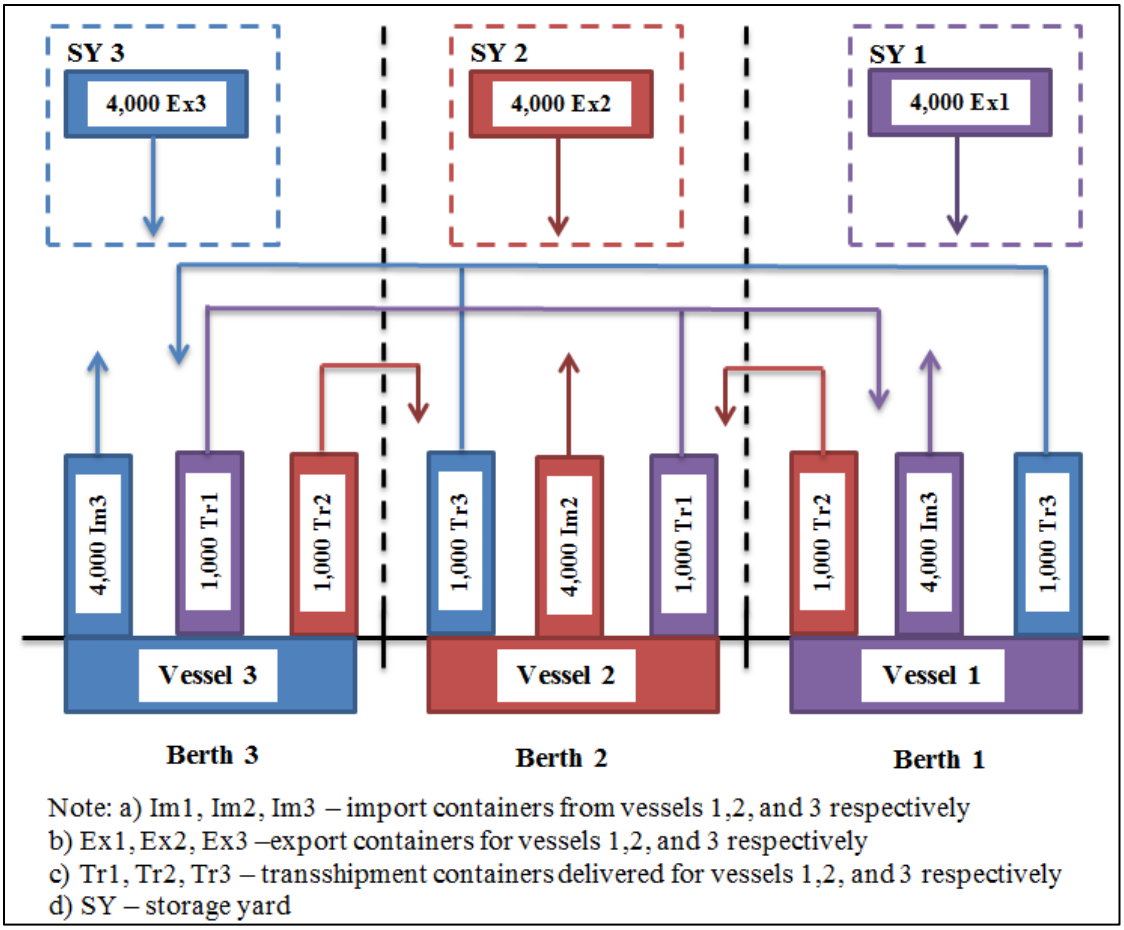


Figure 8. Container Flows at Terminals

On-shore and off-shore QC productivity (QCP) was assumed to follow a triangular distribution [triangular (1.0, 1.5, 3.0) minutes per container move], which translates to a mean (nominal) value of 40 moves/hour/QC (Liftech, Inc., 2007). The triangular distribution, its bounds and mode were chosen based on the literature review (Petering, 2009; Petering & Murty, 2008; Petering et al., 2009). Workload between QCs for each vessel is equally distributed in both simulation models, as this policy increases productivity by minimizing vessel handling time (Song, Cherrett, & Guan, 2012). It was further assumed that the stowage plan for each vessel satisfies stability conditions (e.g.,

stack weight limit, moment equilibrium between bow and stern and between the left and right side of the vessel).

ITV characteristics. Two types of ITVs (yard trucks or YTs and automated lifting vehicles or ALVs) are assumed to carry containers between the quayside and the storage yard (see Figure 7). Each terminal configuration can use only one type of vehicles (either YT or ALV). Usually the speeds of empty and laden YTs are 40 and 25 km/h respectively (Petering, 2009; Petering & Murty, 2008; Petering et al., 2009). In this study YTs speed was set constant and equal to 30 km/h. It is assumed that ALVs have the same speed = 30 km/h (Yang, Choi, & Ha, 2004). ITVs are assumed to carry one 20 foot (ft.) container but other container types can be introduced in both models (e.g., 20 ft., 40 ft., 45 ft., etc.) as well.

Vessels are served by three gangs of ITVs (either YTs or ALVs), each dedicated to serving the QCs of a particular berth. Several studies confirm that this multi-crane oriented (a.k.a. pooling) strategy, when ITVs are shared between QCs serving the same vessel, is more efficient (Park, Dragovic, & Kim, 2009; Petering, 2010; Zeng, Yang, & Lai, 2009). Productivity of QCs with a multi-crane oriented strategy is approximately 20% to 25% higher than the strategy, when ITVs are not shared, most likely due to the increase of QC and ITV dual cycling.

ITV deployment. The ITV deployment strategy, used in this study, is depicted in Figure 9 for both YTs and ALVs. The main differences between the two deployment strategies are: a) QCs do not have to wait for an ALV to become available to unload a container, and b) ALVs do not have to wait for a QC to pick up the container, they are delivering to the quayside. Once a QC picks up a container from a vessel (Figure 9A and 9B), it searches for the first available ITV to load the container. If more than one ITVs are available, the model will assign the container to the ITV closest to the QC at the given simulation time. If idling ITVs are not available, the QC will either wait for the first available YT or, for the ALV case, unload the container to the buffer area. If there is only one idling ITV, it will be assigned to the first available job (i.e., minimization of waiting time for QCs). A similar deployment strategy is applied for export/transshipment containers moved from the storage yard to the quayside (see Figure 9C and 9D). The model computes distances between QCs, ITVs, and GCs based on a road network in the terminal. If a road network does not exist, the model estimates distances based on centroids.

When a loaded ITV enters a yard block, it travels along the handling lane to the assigned GC (see Figure 10). An empty ITV shuffles to the bypass lane. While YTs need to wait for a GC to pick up/place the container from/to their chassis, ALVs are capable of (un)loading the container from/to the handling lane without waiting for a GC service (which increases productivity).

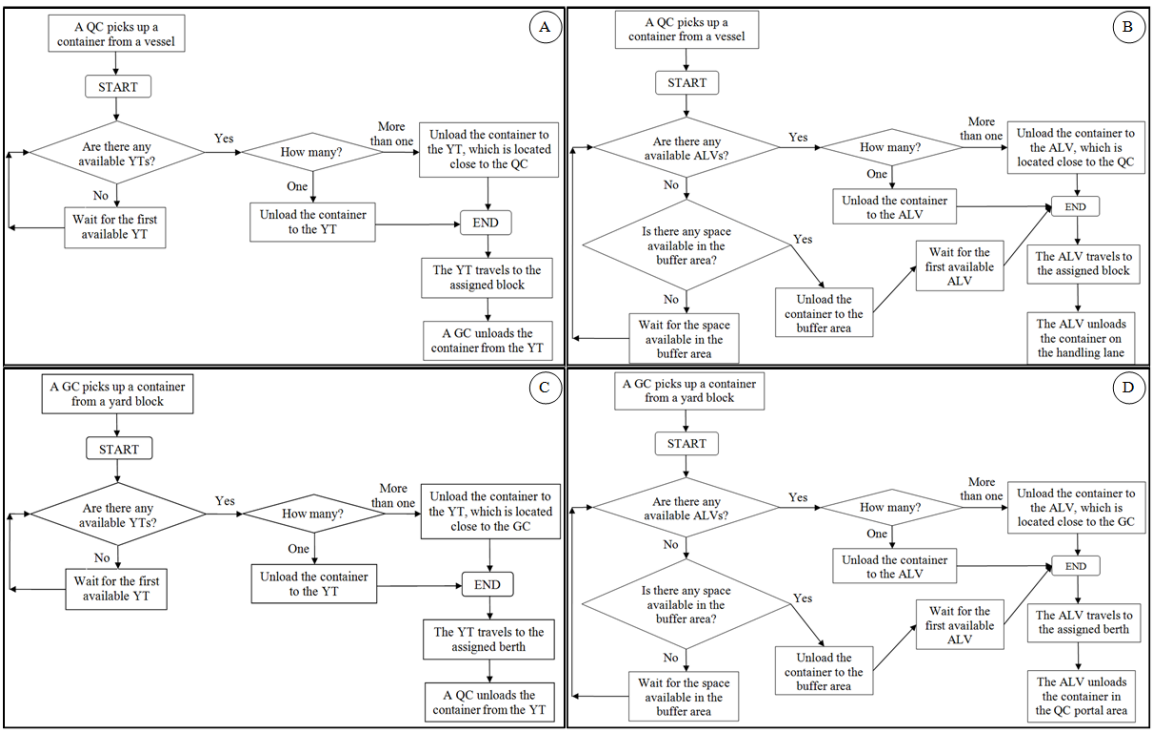


Figure 9. ITV Deployment Strategy

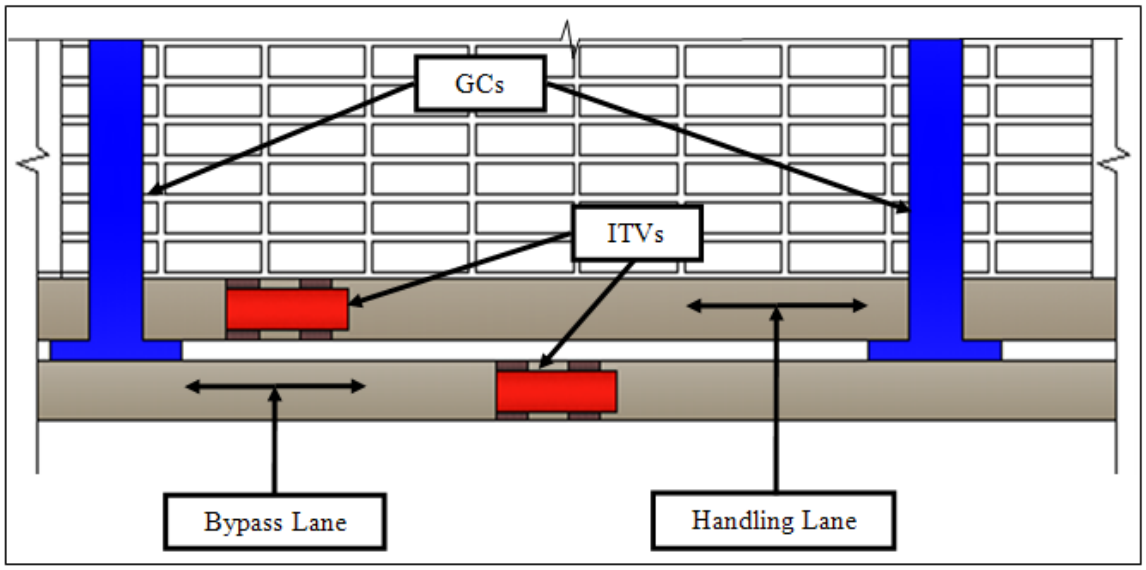


Figure 10. ITVs in the Yard Block

Quayside and storage yard buffer areas. Quayside and storage yard buffer areas of MCT serve three functions: a) an area for cranes to operate on, b) an area for ITV circulation, and c) an area for drop-off/pick-up of containers (by QCs, GCs, and ITVs). Based on preliminary simulation experiments the optimal size of both buffer areas was determined and findings were similar to Vis and Harika (2004). Specifically, the buffer area size at quayside significantly affected QCP, but the buffer area size at the storage yard didn't result in any substantial difference. The buffer area capacity at the quayside and storage yard was set equal to three containers per QC and two containers per storage block, respectively.

Storage yard configuration. The storage yard consisted of 30 and 15 yard blocks (10 and 5 blocks per berth) for CMT and FMT respectively. The storage yard size at FMT was set smaller as transshipment containers are stored on barges. Each storage area at CMT has separate yard blocks dedicated to import, export, and transshipment containers. The capacity of each block was assumed to be 600 TEUs (6 rows x 5 tiers x 20 bays). Length of each bay was assumed equal to 24 ft. (including 4 ft. of clearance space). GCs (un)load containers from ITVs from/to the assigned yard block based on the type of container (export, import, and transshipment). This particular terminal layout was chosen as it reduces the total distance traveled by ITVs and thus task completion time of ITVs, QCs, and GCs (Mohseni, 2011). Import containers were allocated to the blocks, situated closer to the gates. Transshipment containers were placed to the blocks, located closer to the quayside.

Export containers were allocated on the side blocks of each storage area. Exports are transported by DTs, passing through the terminal gates. DTs deliver export containers

to assigned yard blocks, once the space is available (queuing occurred when the space was not available). Then GCs unload containers from DTs to the assigned yard blocks.

Storage yard handling equipment. A group of rubber-tyred GCs is assigned to each storage area. Container stacking and retrieval times are assumed to follow a triangular distribution (Petering, 2009; Petering & Murty, 2008; Petering et al., 2009) with a nominal value of 20 moves/hour [triangular (2.5, 3.3, 3.0)], including reshuffling time required by a GC to retrieve a container.

Optimal QCP determination. The size of each ITV gang and GC group, required to obtain the optimal QCP for the two terminal types (CMT and FMT) under normal operating conditions, was determined based on simulation runs, where the number of ITVs was changed from 1 to 40 and the number of GCs from 1 to 30, both with an increment of one. Note that optimal and nominal QCP values differ as the latter is estimated based on the assumption that QCs will handle containers continuously. The optimal QCP will be less than or equal to the nominal productivity, as it depends on the volume of containers and resources (ITVs and GCs) allocated to serve QCs (i.e., a QC may have to wait for an YT to become available to pick up a container).

Disruptive event assumptions. Taking into account the growing international seaborne trade, it is important for port operations to exhibit resilience to potential man-made and natural disrupting events (Barker, Pant, Baround, & Landers, 2011; Gajjar, Wakeman, & Saloum, 2008; Rose & Wei, 2010). The scope of this research included comparison of the two terminal configurations not only under normal (as discussed previously), but also under disruptive operating conditions.

In this study two disruptive events were assumed for each type of container terminal:

- Disruption A: 33.3% of on-shore QCs and GCs are not available for 12 hours
- Disruption B: 50.0% of on-shore QCs and GCs are not available for 24 hours

Note that damaged QCs and GCs will be available to handle containers at full capacity immediately after the end of the each disruption. For each disruptive event the following assumptions were made as to their effect on the terminal operations:

- Disruptions occur at the simulation time of zero (the beginning of each simulation run);
- A disruptive event is assumed to affect the gate area, i.e., export containers will not be delivered to the terminal and import containers will not be picked up by DTs during the event;
- ITVs are not damaged by the disruptive event. Even in the case where ITVs are potentially affected, they can be replaced (which may be difficult in the cases of damaged GCs or QCs) as terminal operators usually have more ITVs than required for daily operations (to account for downtime/maintenance);
- In the cases of disruptive events, floating QCs will handle a portion of the import containers to compensate for the lost productivity at the quayside;
- When import containers are handled by floating QCs, they will be placed on barges, and stored at the floating yard. Once the vessels depart the port these import containers can be unloaded by QCs or mobile harbor cranes;
- The number of container barges is sufficient to handle the import and transshipment containers;

- Disruptive events were assumed to affect only landside operations. Disruptions, causing breakdowns of seaside operations (e.g., tsunami), will result in a complete terminal (both CMT and FMT) shutdown. Storage yard operations will be still possible, however, vessels cannot be moored and served;
- Disruptive events have deterministic features (i.e., fixed duration and start time, the quantity of damaged equipment is known). Analysis of stochastic disruptive events can be conducted using developed simulation models as well, and is left for the future research.

Computational Experiments

The goal of the computational experiments was to evaluate productivity (makespan of vessel service and QC moves per hour) of the two terminal configurations under normal and disruptive operating conditions. Twenty-four scenarios (shown in Table 5) were developed to model both CMT and FMT under normal operating conditions considering different: a) container composition, b) number of on-shore QCs, and c) number of floating QCs at FMT. Sixteen additional scenarios (shown in Table 6) were developed to analyze performance of both terminal types under disruptive conditions with different: a) container composition, b) number of floating QCs at FMT, and c) quantity of damaged equipment. Completion time of all vessel handling (i.e., makespan) was selected as the simulation stopping criterion which may result in final states of the simulation models under disruptions that differ from the normal operating conditions (i.e., import containers may be stored at the floating yard, when vessel service is completed). However, under disruptive events vessel completion time is the critical component of terminal operations, and as such, the selected stopping criterion does not

limit the validity of the research and results, presented in this study. In most cases, the terminal operator will utilize available resources to move import containers, from the floating to the storage yard blocks, during low demand periods and once operations are back (or close) to normal.

Ten replications for each scenario were used to estimate average values of the various performance measures (presented next). The number of replications was found to be sufficient, as the average standard deviation over all scenarios was less than 0.5% of the mean (Pritsker & Pegden, 1979). Simulation speeds averaged 170 min/sec. Depending on the models' complexity, the simulation software package used in this study (i.e., FlexSim) allows for speeds up to 200,000 time units/sec. The fact that the model speeds are low indicates high complexity.

Numerical data

Normal operating conditions. Data for each one of the 24 scenarios used under normal operating conditions are shown in Table 5, where columns one through nine show: 1) scenario number, 2) terminal type, 3) ITV type, 4) percentage of transshipment containers, 5) total number of QCs, 6) number of on-shore QCs at each berth, 7) number of floating QCs at each berth, 8) number of ITVs for each gang, and 9) number of GCs at the storage area. For example, in the second scenario (S_2) 4 QCs (all located on-shore), 10 YTs, and 15 GCs are assigned to serve each vessel at each berth of CMT. The total demand for each vessel is 12,000 TEUs with an equal split between import and export containers. The quantity of transshipment containers varies by scenario (Table 5, column 4).

For instance, in the first scenario (S_1) 4,000 import and 2,000 transshipment containers are unloaded from each vessel, and 4,000 export and 2,000 transshipment containers are loaded to each vessel. In the second scenario (S_2) 3,000 import and 3,000 transshipment containers are unloaded from each vessel, and 3,000 export and 3,000 transshipment containers are loaded to each vessel.

Table 5
Scenario Analysis under Normal Operational Conditions

Scenario *(1)*	**Terminal Type** *(2)*	**ITV Type** *(3)*	**Transshipment (% of total volume)** *(4)*	**#QCs** *(5)*	**#On-shore QCs** *(6)*	**#Off-shore QCs** *(7)*	**# ITV** *(8)*	**# GCs** *(9)*
S_1	CMT	YT	33.3	3	3	0	8	13
S_2			50.0	4	4	0	10	15
S_3			40.0	5	5	0	13	19
S_4			33.3	6	6	0	15	21
S_5			50.0		6	0	16	23
S_6		ALV	33.3	3	3	0	7	11
S_7			50.0	4	4	0	8	14
S_8			40.0	5	5	0	10	17
S_9			33.3	6	6	0	12	19
S_10			50.0		6	0	13	20
S_11	FMT	YT	33.3	3	2	1	5	6
S_12			25.0	4	3	1	6	12
S_13			50.0		2	2	4	6
S_14			40.0	5	3	2	6	12
S_15			60.0		2	3	4	6
S_16			33.3	6	4	2	8	14
S_17			50.0		3	3	6	12
S_18		ALV	33.3	3	2	1	3	4
S_19			25.0	4	3	1	5	11
S_20			50.0		2	2	3	4
S_21			40.0	5	3	2	5	11
S_22			60.0		2	3	3	4
S_23			33.3	6	4	2	7	12
S_24			50.0		3	3	5	11

Note that sizes of ITV gangs and GC groups, required to obtain the optimal QCP, were determined based on simulation runs. An example of the procedure for estimating the necessary numbers of ITVs and GCs is presented in Figure 11 for the case of 3 QCs at both CMT and FMT. Each graph provides the following information: a) number of GCs (x-axis), b) number of ITVs (y-axis), c) obtained QCP (z-axis), d) scenario number (top right edge), e) optimal ITV and GC combination (depicted in the top left edge and labeled by “●“).

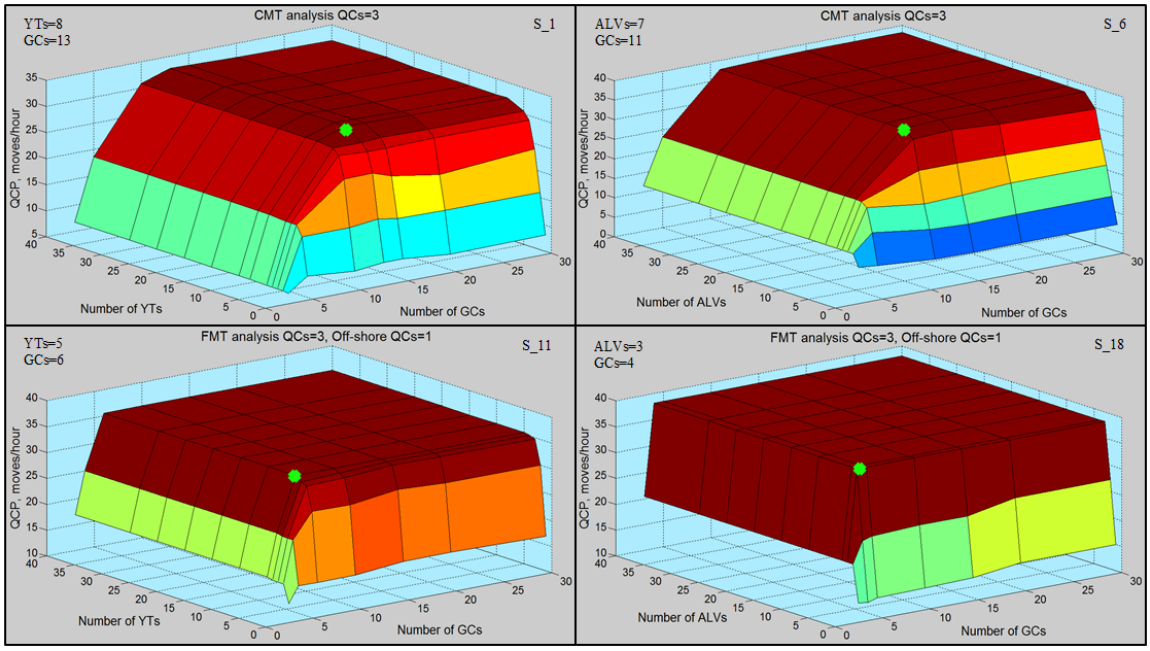


Figure 11. Procedure for Estimating Quantity of Required ITVs and GCs

For instance, in the first scenario 8 YTs and 13 GCs provided the optimal QCP = 32.66 moves per hour at CMT with 3 on-shore QCs (see S_1). Similar analysis was conducted for each scenario (see Table 5). It was found that on average CMT required 2.61 YTs per QC, 2.11 ALVs per QC, 3.89 GCs per QC for models with YT deployment, and 3.44 GCs per QC for models with ALV deployment. As for FMT, 2.05

YTs per QC, 1.63 ALVs per QC, 3.58 GCs per QC for models with YT deployment, and 3.00 GCs per QC for models with ALV deployment were required to obtain the optimal QCP. Thus, on average under normal operating conditions FMT required 21.4% less YTs, 22.7% less ALVs, 8.0% less GCs for models with YT deployment, and 12.9% less GCs for models with ALV deployment (savings are presented per QC).

Disruptive operating conditions. Scenarios, used for analysis of CMT and FMT productivity under disruptive scenarios, are presented in Table 6, where columns one through nine show: 1) scenario number, 2) terminal type, 3) ITV type, 4) disruption, 5) percentage of transshipment containers, 6) number of operational on-shore QCs at each berth, 7) number of operational off-shore QCs at each berth, 8) number of ITVs for each gang, and 9) number of GCs at the storage area. Scenarios labeled as "No Disruption" (e.g., S_1*, S_2*, S_7*, etc.) are identical to the ones used for modeling normal operating conditions (see Table 5, scenarios S_4, S_5, and S_9, respectively). Note that Table 6 presents the quantity of equipment, operational without breakdowns. For example, in the third scenario (S_3*) 4 on-shore QCs (2 QCs are damaged and become available after 12 hrs), zero off-shore QCs, 15 YTs, and 14 GCs (7 GCs are damaged and become available after 12 hrs) are assigned to serve a vessel at each berth. The total demand for each vessel is 12,000 TEUs with an equal split between import and export containers as with normal conditions. The quantity of transshipment containers varies by scenario (Table 6, column 5).

For instance, in the first scenario (S_1*) 4,000 import and 2,000 transshipment containers are unloaded from each vessel, and 4,000 export and 2,000 transshipment containers are loaded to each vessel. In the second scenario (S_2*) 3,000 import and 3,000 transshipment containers are unloaded from each vessel, and 3,000 export and 3,000 transshipment containers are loaded to each vessel. Next the analysis of simulation results is presented.

Table 6
Scenario Analysis under Disruptive Operational Conditions

Scenario *(1)*	**Terminal Type** *(2)*	**ITV Type** *(3)*	**Disruption** *(4)*	**Transshipment (% of total volume)** *(5)*	**#On-shore QCs** *(6)*	**#Off-shore QCs** *(7)*	**# ITV** *(8)*	**# GCs** *(9)*
S_1*	CMT	YT	No Disruption	33.3	6	0	15	21
S_2*			No Disruption	50.0	6	0	16	23
S_3*			A	33.3	4	0	15	14
S_4*			A	50.0	4	0	16	15
S_5*			B	33.3	3	0	15	10
S_6*			B	50	3	0	16	11
S_7*		ALV	No Disruption	33.3	6	0	12	19
S_8*			No Disruption	50	6	0	13	20
S_9*			A	33.3	4	0	12	12
S_10*			A	50	4	0	13	13
S_11*			B	33.3	3	0	12	9
S_12*			B	50	3	0	13	10
S_13*	FMT	YT	No Disruption	33.3	4	2	8	14
S_14*			No Disruption	50	3	3	6	12
S_15*			A	33.3	2	2	8	10
S_16*			A	50	1	3	6	8
S_17*			B	33.3	1	2	8	7
S_18*			B	50	0	3	6	6
S_19*		ALV	No Disruption	33.3	4	2	7	12
S_20*			No Disruption	50	3	3	5	11
S_21*			A	33.3	2	2	7	8
S_22*			A	50	1	3	5	7
S_23*			B	33.3	1	2	7	6
S_24*			B	50	0	3	5	5

Makespan analysis. The vessel service time makespan was chosen as the first performance measure to compare CMT and FMT operations under normal and disruptive conditions.

Normal operating conditions. Figure 12 presents the vessel service time makespan under normal operating conditions for all 24 scenarios. The x-axis label has three components: a) scenario, b) number of on-shore and off-shore QCs, and c) percentage of transshipment containers. For example, in the upper left graph of Figure 12 the first bar shows the makespan (122.5 hrs.) at CMT with YT deployment, where 3 on-shore and zero off-shore QCs serve each vessel, where transshipment containers are equal to 33.3% of the total demand (scenario S_1).

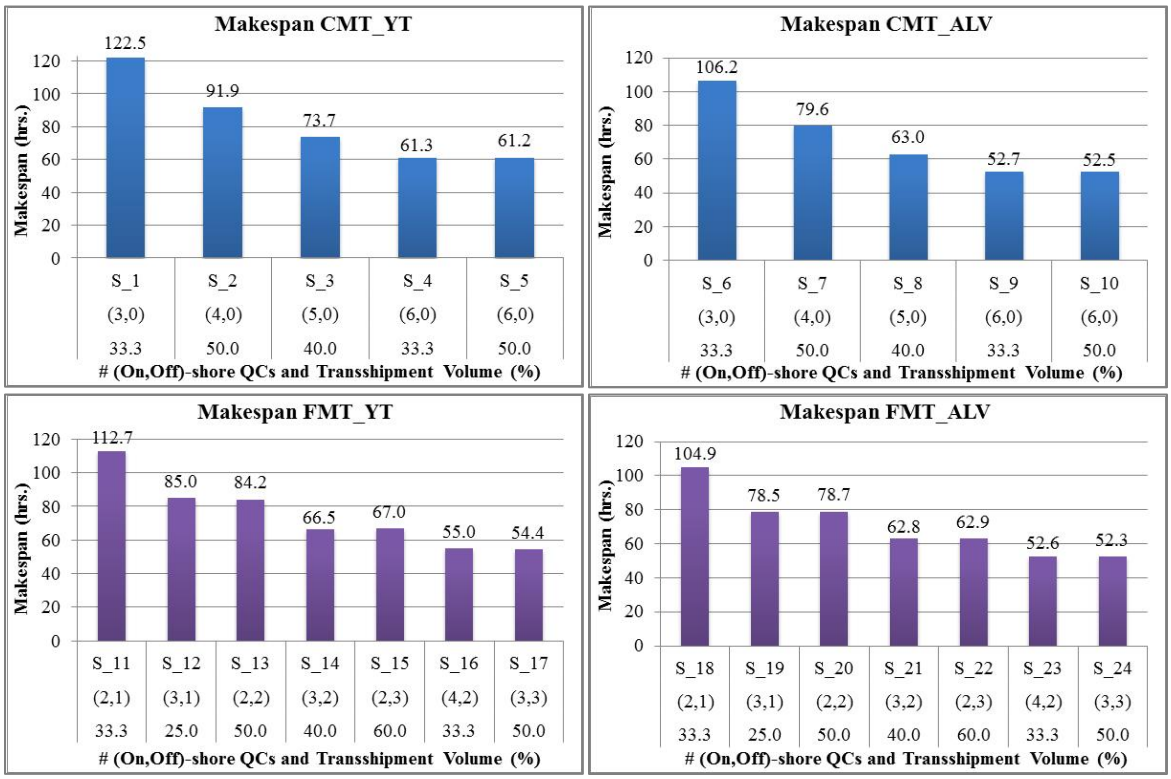


Figure 12. Makespan under Normal Operational Conditions by Terminal Type, ITV Configuration, and Transshipment Volumes

FMT provided faster vessel service for all scenarios and on average, FMT makespan savings comprised 7.6 hrs. (or 9.5%) for YT deployment models and 0.5 hrs. (or 0.6%) for ALV deployment models. ALV deployment models outperformed YT deployment models in terms of makespan. However, FMT makespan savings were not substantial for cases when ALVs were employed as ITVs. The latter can be explained by the fact that ALVs are more productive than YTs, and were able to provide more efficient container handling at both CMT and FMT under normal operating conditions. FMT configuration also provided faster vessel service (than CMT) with less equipment for scenarios with higher transshipment volumes (see S_13, S_15, S_20, and S_22).

Disruptive operating conditions. Several researchers quantified resilience of MCTs based on the difference in terminal productivity (e.g., vessel service time makespan) before and after disruptive events (Barker et al., 2011; Gajjar et al., 2008; Rose & Wei, 2010). In this study vessel service completion makespan was selected as the key performance measure to assess effects of the disruptive events. Figure 13 presents the vessel service time makespan for all 24 scenarios. The x-axis label has two components: a) ITV type, and b) percentage of transshipments. For example, YT-33.3% refers to the simulation model with YT deployment and 33.3% of all TEUs handled being transshipment containers.

ALV deployment models outperformed YT deployment models in terms of makespan. For all scenarios CMT was affected more by the disruptive events (i.e., higher makespan). CMT YT deployment models were the most vulnerable to disruptive events with a makespan increase, as compared to normal operating conditions, averaging 10.6 hrs. (or 17.3%) and 19.1 hrs. (or 31.2%) for disruptions A and B respectively. CMT ALV

deployment models were less affected by the disruptions with a makespan increase, as compared to normal operating conditions, averaging 7.1 hrs. (or 13.4%) and 13.7 hrs. (or 26.0%) for disruptions A and B respectively. FMT YT and ALV deployment models resulted in similar makespan increase (as compared to normal operating conditions), averaging 5.8 hrs. (or 10.8%) and 12.5 hrs. (or 23.4%) for disruptions A and B respectively. The latter results may be explained by the fewer number of ITVs and GCs used at the FMT model in scenarios with ALV deployment. For both disruptions (A and B) the FMT with YT deployment model provided substantially higher makespan savings when compared to ALV deployment, while scenarios with lower transshipment percentages showed smaller improvements.

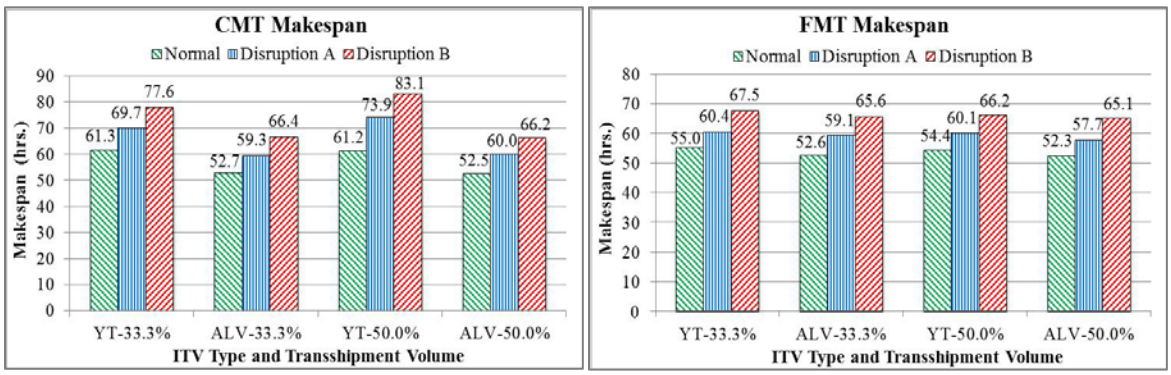


Figure 13. Makespan under Normal & Disruptive Operational Conditions by Terminal Type, ITV Configuration, and Transshipment Volumes

QCP analysis. QCP (on- and off-shore combined) was selected as the second performance measure of CMT and FMT operations under normal and disruptive conditions. QCP is important to terminal operators as their agreements with liner shipping companies usually contain a clause on container handling rates.

Normal operating conditions. Figure 14 shows QCP (moves per hour by QC) for all 24 scenarios, under normal operating conditions at both terminals. Labels on the x-axis show: a) scenario, b) number of on- and off-shore QC available at each berth, and c) percentage of transshipment containers assigned to each vessel. For instance, in the upper left graph of Figure 14 the first bar presents QCP (32.7 moves/hour) at CMT with YT deployment, where 3 on-shore and zero off-shore QCs serve each vessel with 33.3% of transshipment containers (scenario S_1). On average, CMT provided QCP of 32.6 moves/hour for YT deployment models and 37.9 moves/hour for ALV deployment models. As for FMT, the average QCP was 35.9 moves/hour and 38.2 moves/hour for YT and ALV deployment models respectively.

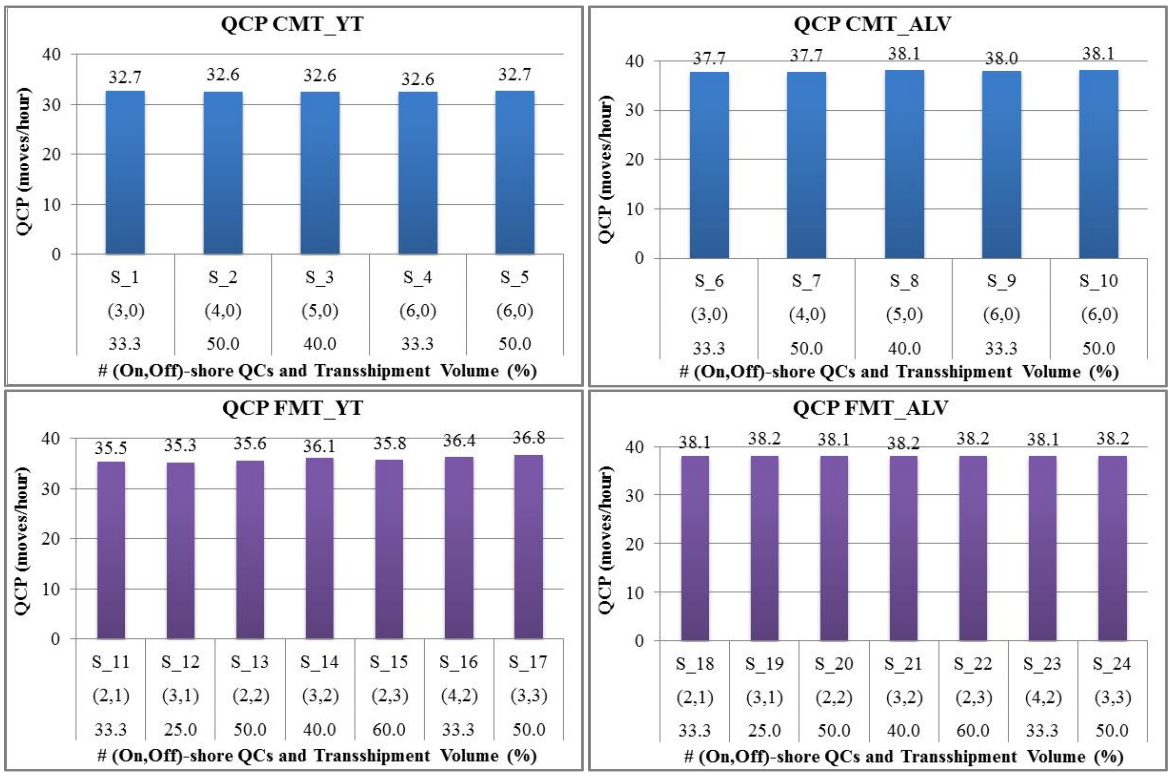


Figure 14. QCP under Normal Operational Conditions by Terminal Type, ITV Configuration, and Transshipment Volumes

Disruptive operating conditions. Figure 15 presents QCP (moves per hour by QC) for all 24 scenarios, under disruptive operating conditions at both terminals. Labels on the x-axis show: a) scenario, b) number of on- and off-shore QC available at each berth, and c) percentage of transshipment containers assigned to each vessel. For example, in the upper left graph of Figure 15 the first bar denotes QCP (32.6 moves/hour) at CMT with YT deployment, where 6 on-shore and zero off-shore QCs serve each vessel with 33.3% of transshipment containers (scenario S_1*).

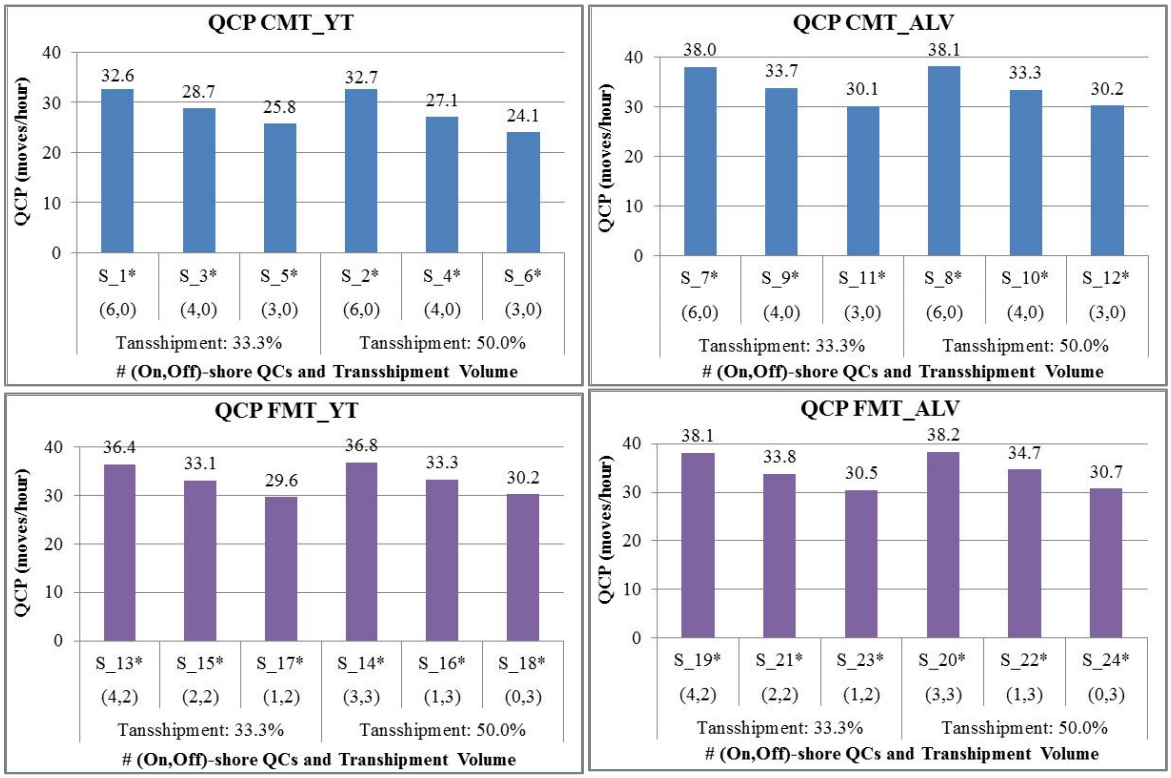


Figure 15. QCP under Normal & Disruptive Operational Conditions by Terminal Type, ITV Configuration, and Transshipment Volumes

FMT exhibits significantly higher QCP for the cases, where YTs are employed. The same trend does not apply to ALV deployment models, when similar QCPs were

obtained at CMT and FMT. This can be explained by the fact that ALVs are more productive than YTs, and were able to provide more efficient container handling at both CMT and FMT under normal and disruptive conditions.

Storage of import containers at the floating yard. Another performance measure, quantified by this study, was the volume of import containers unloaded to feeder barges and stored at the floating yard during the disruptive event. The amount of imports, stored on barges at the floating yard, was recorded at each simulation run and average values are presented in Figure 16. Labels on the x-axis show: a) scenario, b) ITV type, and c) percentage of transshipments. On average 49.0% more import containers were placed on barges under disruption B as compared to A. This can be expected as on-shore QCs are out of service for a longer time period during the former disruptive event, utilization of floating QCs for handling imports increases. Approximately 12% less import containers were stored at the floating yard for ALV deployment models as compared to YT deployment models, since more containers could be processed by QCs and GCs (ALVs do not have to wait for the container to be (un)loaded). Note that the strategy of storing imports at the floating yard was crucial for improving FMT productivity, as otherwise idling time of floating QCs along with makespan would substantially increase.

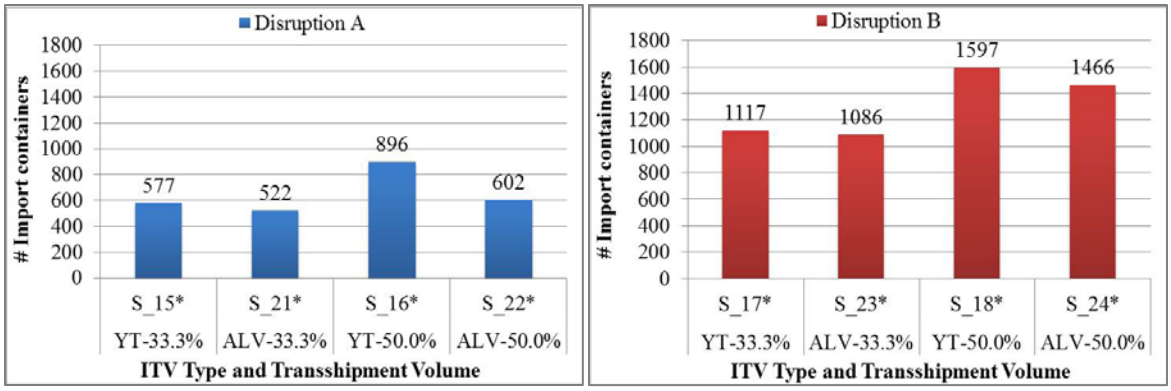


Figure 16. Import Containers Stored on Barges during Disruptions

Economic analysis. A 20-year cost analysis for CMT and FMT was based on the estimation of initial investments and operational costs for both systems. Investment costs included site development costs (e.g., clean and grub, civil site works, wharf construction, site electrical, yard lightening, gate site work, gate facility, maintenance and administration buildings, etc.) and equipment costs (i.e., on-shore QCs, off-shore QCs, ITVs, GCs, crane barges, and container barges). Site development costs for two terminal configurations were computed using guidelines, provided by Wilbur Smith Associates (2001). Equipment costs were calculated using brochures, released by manufacturers (Shanghai Zhenhua Heavy Industry Co., CNBM International Engineering Co., Kalmar Industries, etc.). Operational costs covered maintenance, insurance, QC gangs, ITV gangs, GC gangs, and push boat operators (Pielage et al., 2008). Note that investment and operational costs vary from terminal to terminal.

The amount of necessary equipment, estimated by simulation models, was used as input for calculating associated costs (see Table 5). Results of the economic analysis are presented for 24 considered scenarios (only normal operating conditions) in Figure 17. The total costs were estimated per berth of CMT or FMT for a given quantity of QCs. For

instance, the blue line with abbreviation CMT_YT(33.3) at the top left graph of Figure 17 indicates that the total expenses (including investment and operational costs) for CMT with YT deployment and 33.3% of transshipment comprise $454.3 million at the end of the considered time horizon (i.e., at year 20).

Results of the economic analysis indicate that ALV deployment models have a higher capital investment but lower operational costs than YT deployment models. Pay back periods for ALV deployment models didn't exceed 2 years, assuming 80% QC utilization (7008 operational hours/year) for both FMT and CMT. CMT with YT deployment was found to be the most expensive alternative for all scenarios. FMT site development costs were lower than CMT site development costs (mainly due to larger size of the storage yard), but higher equipment investment costs (mainly due to the cost of a crane barge at FMT, which could comprises 10-12 million USD). FMT average savings over 20-year horizon comprised $66.7 million for YT deployment models and $15.0 million for ALV deployment models. FMT operational costs were lower than CMT operational costs for cases with high percentage of transshipment containers. Advantages of FMT over CMT substantially decreased with the demand reduction for transshipment containers.

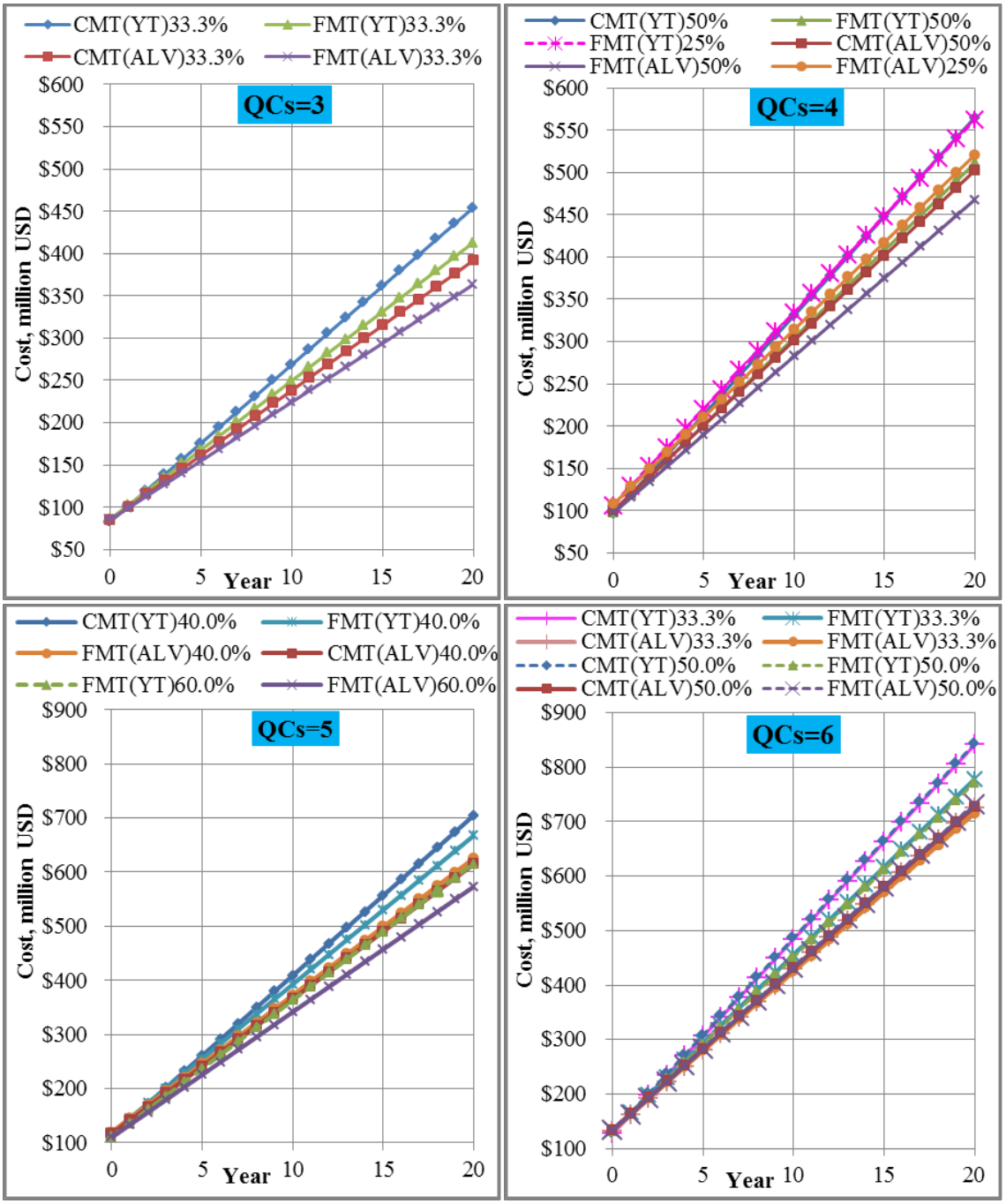


Figure 17. Economic Analysis

Conclusions and Future Research Avenues

As a part of this dissertation, the floaterm concept was evaluated as means to increase productivity of MCT operations and improve their resilience. Two simulation

models were developed to compare performance of a conventional marine container terminal to one that has adopted the floaterm concept under normal and disrupted operating conditions. From the analysis significant savings in the makespan of vessel completion time were observed under both operating conditions for FMT as compared to CMT. Benefits of the floaterm concept increased with transshipment volumes. The latter observation should be expected as the main purpose of the floaterm concept is to relieve landside operations from handling of transshipments containers, while at the same time act as a buffer storage area for import containers, when disruptive events limit the (un)loading capacity of on-shore QCs. Research outcomes indicated that FMT demonstrated substantial cost and vessel service makespan savings for scenarios with YT deployment. Although FMT with ALV deployment did not significantly outperform CMT in terms of vessel service makespan, for the majority of cases it yielded significant cost savings.

Even though simulation, as a modeling tool, offers a number of advantages, the models developed herein inherit a number of limitations common amongst marine container terminal simulation models found in the literature. These limitations include: a) capturing ITV interference (Petering et al., 2009); b) implementing optimal ITV deployment strategies, c) accounting for terminal congestion, and d) modeling different storage yard strategies and areas for hazmat, overweight, oversized, and refrigerator containers. These drawbacks can be addressed as part of future research, and do not reduce the validity of the research outcomes, presented herein. Addressing these limitations will most likely increase the estimated benefits of the floaterm concept under normal and disruptive operating conditions.

4. BERTH ALLOCATION AND SCHEDULING AT DEDICATED MARINE CONTAINER TERMINALS WITH EXCESSIVE DEMAND

Introduction

This chapter proposes and evaluates a new contractual agreement between dedicated and multi-user terminal operators for improving productivity of the former marine terminal, which does not have enough capacity for service of its vessels. The contractual agreement allows a dedicated (or private) container terminal (DCT) to divert vessels to a multi-user (or public) container terminal (MUT). The problem is formulated as a non-linear mixed integer program, and a Memetic Algorithm is proposed as the solution algorithm. The objective of the suggested model is to determine vessel assignment (calling at DCT) at both DCT and MUT, while minimizing handling and delayed departure vessel costs for the DCT operator.

Problem Description

The problem, addressed in this study, is an extension of the model, proposed by Imai et al. (2008), where vessels with excessive waiting times were diverted from a multi-user terminal to an external terminal. Unlike the study by Imai et al. (2008), where decision on vessel diversion was based on the vessel waiting time, the berth scheduling policy proposed herein diverts vessels based on a more generalized cost function (that can include the vessel waiting time). Furthermore, the proposed berth scheduling policy imposes a service time window (TW) constraint for each diverted vessel. These TW constraints are adopted to better portray real world operations, where it is highly unlikely, that a terminal operator will accept a vessel from another terminal at any time, as it may

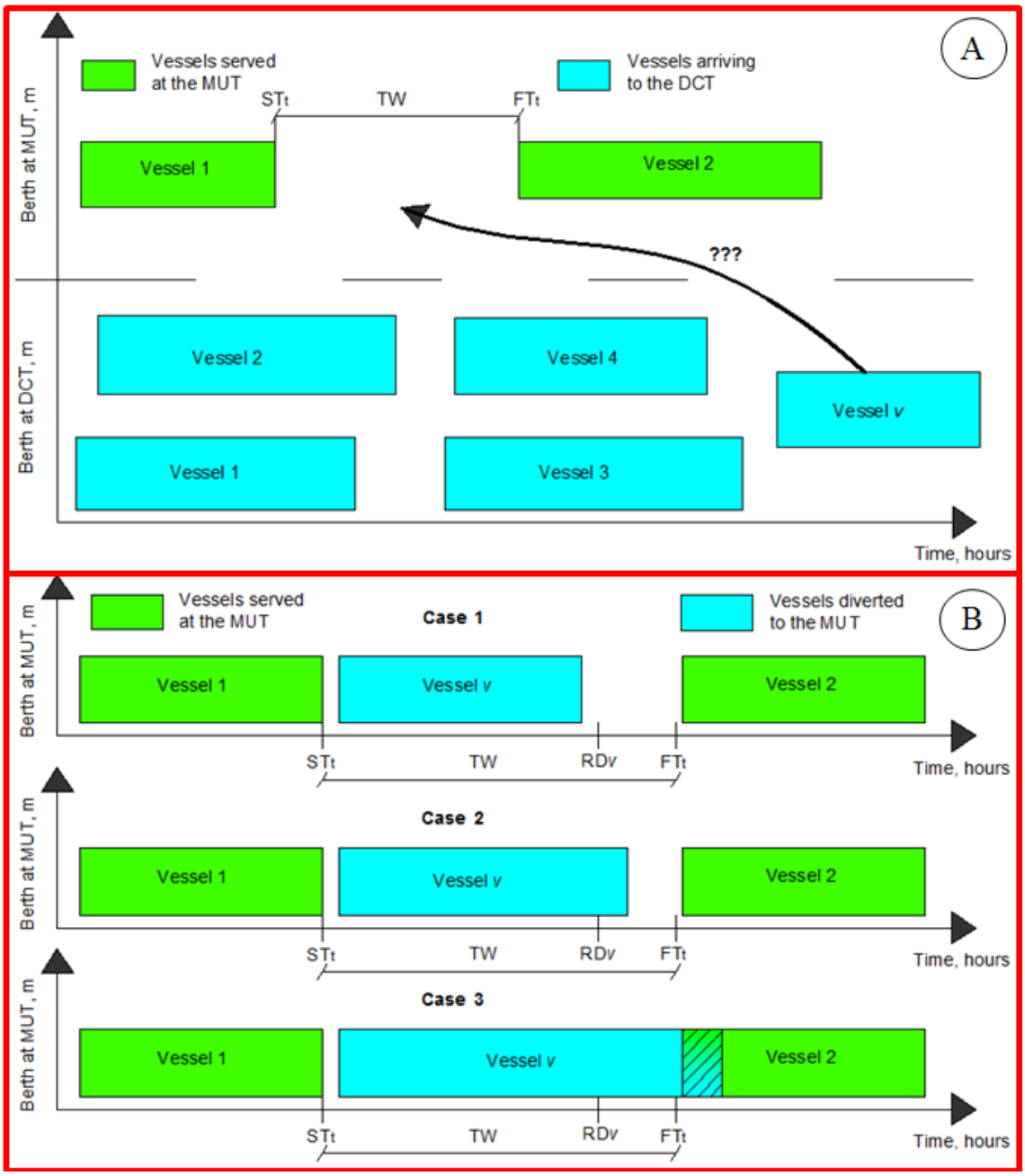
result in service disruption of its customers. Thus, it is more likely that the two terminals will enter an agreement similar to the one described next.

Contractual agreement description. This study considers a marine port with two container terminals: DCT and MUT. The former serves vessels from a particular liner shipping company, while the latter from various liner shipping companies[1]. The DCT operator has a contractual agreement and can divert vessels to MUT. Since MUT also provides service to vessels of other companies, diverted vessels (from DCT) can only be handled during particular TWs (see Figure 18A). For each TW, the MUT operator can offer various handling rates. Vessel handling charges at MUT are proportional to the handling rate (i.e., higher price for higher productivity; the latter is usually measured in TEUs/hr. (un)loaded from/to the vessel). The DCT operator is able to request one of the available handling rates. The latter option allows the DCT operator to weigh different alternatives of delayed departure costs, if a vessel is served at its facility vs. handling costs (and reduced or no delayed departure costs) if a vessel is served at MUT. Note that the MUT operator will not alter its berth schedule to better accommodate the diverted demand (i.e., delay start of service of other vessels or divert resources from other vessels/berths to increase handling rates during a TW). It is assumed that both terminals have discrete berth layouts, and that one vessel can be served at each berth at any given time.

Note that vessel handling time at DCT varies by its berth assignment (see Beirwirth & Meisel, 2010, 2015; Theofanis et al., 2009 for an excellent description of the "preferred berth", vessel service time, location of containers at the storage yard and QC

[1] These assumptions do not limit the generality of the proposed model and can be relaxed as needed (e.g., DCT serves vessels from multiple liner shipping companies)

allocation/scheduling). Next the concept of vessel service at MUT during TWs is described in more detail.



Note st_t and ft_t – start and end of TW, RD_v – requested departure time of vessel v

Figure 18. Suggested Berthing Policy

Service at MUT. If a diverted vessel can be served within a TW at MUT there are two possible scenarios for service completion (see Figure 18B cases 1 and 2 respectively):

1. Vessel service is completed before the requested departure time, and the total service cost is equal to the handling cost and premium (negative cost)[2] due to early vessel departure, and

2. Vessel service is completed after the requested departure time, and the total service cost is equal to the handling cost plus a penalty[3] due to late vessel departure.

If vessel service is completed on time, no penalties/premiums are imposed. It is assumed that a vessel cannot be diverted for service (see case 3 in Figure 18B), if service cannot be completed by the end of the TW under the highest available handling rate. Note that the same waiting and delayed/early departure costs are applied to vessels served at DCT.

Mathematical Formulation

The berth scheduling policy, described in previous section, is formulated as a non-linear mixed integer mathematical model (from now on referred to as ***BSDM***). Next the basic notations, used throughout this chapter, are presented, followed by the mathematical formulation of ***BSDM***. Additional notations will be defined throughout this chapter as needed.

[2] These assumptions do not limit the generality of the proposed model and can be relaxed as needed (e.g., DCT serves vessels from multiple liner shipping companies)

[3] Premiums and penalties refer to the DCT operator costs

Nomenclature

Sets

V	Set of vessels requesting service at DCT
B	Set of berths
T	Set of available TWs at MUT
$R_t, t \in T$	Set of available handling rates of TW $t \in T$ at MUT

Decision variables

$x_{vb}, v \in V, b \in B$	=1 if vessel *v* is served at berth *b* and zero otherwise (at DCT)
$d_{vt}, v \in V, t \in T$	=1 if vessel *v* is diverted for service at MUT during TW *t* and zero otherwise
$y_{ps}, p, s \in V, p \neq s$	=1 if vessel *s* is served at the same berth as vessel *p* as its immediate successor and zero otherwise (at DCT)
$f_v, v \in V$	=1 if vessel *v* is served as the first vessel at the assigned berth and zero otherwise (at DCT)
$l_v, v \in V$	=1 if vessel *v* is served as the last vessel at the assigned berth and zero otherwise (at DCT)

Auxiliary variables

$t_v, v \in V$	start time of service for vessel *v* (at either terminal)
$LD_{v,}\ v \in V$	hours of late departure for vessel *v*
$ED_v, v \in V$	hours of early departure for vessel *v*

Parameters

$A_v, v \in V$	arrival time of vessel *v* (hrs.)
$NC_v, v \in V$	number of containers (un)loaded from/to vessel *v* (TEUs)
$D_{vb}, v \in V, b \in B$	handling rate of vessel *v* at berth *b* at DCT (TEUs/hr.)
$S_{vb} = \frac{NC_v}{D_{vb}}, v \in V, b \in B$	handling time of vessel *v* at berth *b* at DCT (hrs.)
$H_{vt}^r, v \in V, t \in T, r \in R_t$	handling time of vessel *v* during a TW *t* under handling rate r at MUT (hours)
$RD_v, v \in V$	requested departure time of vessel *v* (hrs.)
$hc_v, v \in V$	handling cost of vessel *v* at DCT (USD/hr.)
$hc_t^r, t \in T, r \in R_t$	handling cost at MUT during a TW *t* under handling rate r (USD/TEU)
$dc_v, v \in V$	late departure penalty for vessel *v* (USD/hr.)
$ep_v, v \in V$	early departure premium for vessel *v* (USD/hr.)
$[st_t; ft_t], t \in T$	start and end of a TW *t*
M	large positive number

BSDM:

$$min[\sum_{v\in V}\sum_{t\in T}(NC_v d_{vt} hc_t^r) + \sum_{v\in V}\sum_{b\in B}(S_{vb}x_{vb}hc_v) + \sum_{v\in V}(dc_v LD_v) - \sum_{v\in V}(ep_v ED_v)] \quad (1)$$

Subject to:

$$\sum_{b\in B} x_{vb} + \sum_{t\in T} d_{vt} = 1 \ \forall v \in V \quad (2)$$

$$f_s + \sum_{p\in V\neq s} y_{ps} + \sum_{t\in T} d_{st} = 1 \ \forall s \in V \quad (3)$$

$$l_p + \sum_{s\in V\neq p} y_{ps} + \sum_{t\in T} d_{pt} = 1 \ \forall p \in V \quad (4)$$

$$f_p + f_s + d_{pt} + d_{st} \leq 3 - x_{pb} - x_{sb} \ \forall p, s \in V, p \neq s, b \in B, t \in T \quad (5)$$

$$l_p + l_s + d_{pt} + d_{st} \leq 3 - x_{pb} - x_{sb} \ \forall p, s \in V, p \neq s, b \in B, t \in T \quad (6)$$

$$y_{ps} - 1 \leq x_{pb} + d_{pt} - x_{sb} - d_{st} \leq 1 - y_{ps} \ \forall p, s \in V, p \neq s, b \in B, t \in T \quad (7)$$

$$t_v \geq A_v \ \forall v \in V \quad (8)$$

$$t_v \geq \sum_{t\in T}(st_t d_{vt}) \ \forall v \in V \quad (9)$$

$$ft_t d_{vt} \leq t_v + H_{vt}^r \ \forall v \in V, t \in T \quad (10)$$

$$t_s \geq t_p + \sum_{b\in B}\left(S_{pb}x_{pb}\right) - M\left(1 - y_{ps}\right) \ \forall p, s \in V, p \neq s \quad (11)$$

$$LD_v \geq t_v + \sum_{b\in B}(S_{vb}x_{vb}) - RD_v - M(1 - \sum_{b\in B} x_{vb}) \ \forall v \in V \quad (12)$$

$$LD_v \geq t_v + \sum_{t\in T}(H_{vt}^r \, d_{vt}) - RD_v - M(1 - \sum_{t\in T} d_{vt}) \ \forall v \in V \quad (13)$$

$$LD_v \geq 0 \ \forall v \in V \quad (14)$$

$$ED_v = max(0; \ RD_v - [t_v + \sum_{b\in B}(S_{vb}x_{vb})] - M(1 - \sum_{b\in B} x_{vb})) \ \forall v \in V \quad (15)$$

$$ED_v = max(0; \ RD_v - [t_v + \sum_{t\in T}(H_{vt}^r \, d_{vt})] - M(1 - \sum_{t\in T} d_{vt})) \ \forall v \in V \quad (16)$$

$$d_{vt} \leq PS_{vt} \ \forall v \in V, t \in T \quad (17)$$

$$x_{vb} \in \{0,1\} \ v \in V, b \in B \quad (18)$$

$$d_{vt} \in \{0,1\} \ v \in V, t \in T \quad (19)$$

$$PS_{vt} \in \{0,1\} \ v \in V, t \in T \quad (20)$$

$$y_{ps} \in \{0,1\} \ p, s \in V \quad (21)$$

$$f_v, l_v \in \{0,1\} \ v \in V \quad (22)$$

$$LD_v, t_v, ED_v, NC_v, A_v, D_{vb}, S_{vb}, H_{vt}^r, RD_v, hc_v, hc_t^r, dc_v, ep_v, st_t, ft_t \in R^+ \forall v \in V, t \in T, r \in R_t \quad (23)$$

The objective function (1) minimizes the total handling cost of vessels calling at DCT. The first component of the objective function estimates the handling costs for vessels calling at DCT and served at DCT. The second component of the objective function estimates the handling costs for vessels calling at DCT and served at MUT. The third and fourth components estimate penalties/premiums due to late/early departures of vessels calling at DCT. Constraints set (2) ensure that a vessel is served once either at DCT or MUT. Constraints set (3) indicate that a vessel can either be served first or after another vessel at DCT, or it can be diverted for service at MUT. Constraints set (4) ensure that a vessel can either be served last or before another vessel at DCT, or it can be diverted for service at MUT. Constraints set (5) indicate that only one vessel can be served first at each berth at DCT. Constraints set (6) ensure that only one vessel can be served last at each berth at DCT. Constraints set (7) indicate that a vessel can be served after another, if they are both assigned to the same berth at DCT. Constraints set (8) ensure that handling of a vessel starts only after its arrival. Constraints set (9) indicate that handling of a diverted vessel cannot start before the beginning of a TW. Constraints set (10) ensure that service of a diverted vessel, assigned during a TW under selected handling rate, should be completed before the end of the TW. Constraints set (11) compute service times of vessels at DCT. Constraints sets (12) through (14) estimate late departures, while constraints sets (15) and (16) estimate early departures. Constraints set (17) ensure that a vessel will not be diverted to a TW at MUT, if it cannot be served there during that TW length. Constraints sets (18) through (23) define the decision variables and parameters. Next a heuristic used to select handling rates for each available TW at MUT for a diverted vessel is presented.

Data preprocessing. The optimal handling time of each vessel $\boldsymbol{v} \in V$ calling at DCT at each available TW at MUT can be estimated by preprocessing based on finish times and service costs under each available service rate $r \in R_t$ and TW $t \in T$. Let VFT_{vt}^r and $OCDV_{vt}^r$ denote the finish time and service cost (handling and delayed/early departure) of vessel $v \in V$, served at MUT during time window $t \in T$ under handling rate $r \in R_t$. The optimal handling rate for each vessel at each available TW (SR_{vt}) will be the one with the minimum service cost ($OCDV_{vt}^r$). During preprocessing the parameter PS_{vt} is calculated. The pseudocode of the vessel handling rate estimation (***VHRE***) is presented next.

VHRE Pseudocode

Set $VFT_{vt}^r = 0; OCDV_{vt}^r = 0; SR_{vt}^r = 0; PS(v,t) = 0;\ \forall v \in V, t \in T,\ r \in R_t$

for $\forall v \in V, t \in T,\ r \in R_t$ set

$$VFT_{vt}^r = max(st_t; A_v) + \left(\frac{NC_v}{r}\right)$$

$$OCDV_{vt}^r = (NC_v \times hc_t^r) + max(VFT_{vt}^r - RD_v; 0) \times dc_v - max(RD_v - VFT_{vt}^r; 0) \times ep_v$$

$$SR_{vt}^r = arg\,\underset{r}{min}(OCDV_{vt}^r)$$

if $VFT_{vt}^r \leq ft_t$

$PS(v,t) = 1$

else

$PS(v,t) = 0$

end

end

end

Solution Approach

Even simple discrete berth scheduling problem formulations are difficult to solve (Carlo et al., 2013) as they belong to the NP problems class (formulations can usually be reduced to the machine scheduling problem). In this study a Memetic Algorithm (***MA***) was developed to obtain good quality solutions within acceptable computational time. ***MAs*** belong to the group of Evolutionary Algorithms (***EAs***), and are widely used for solving complex problems in different fields (Dasgupta & Michalewicz, 1997; Eiben &

Smith, 2003; Golias et al., 2010; Sivanandam & Deepa, 2008, etc.). While ***EAs*** construct individuals using stochastic operators, ***MAs*** also employ local search heuristics and (usually) provide higher quality solutions and faster convergence (Eiben & Smith, 2003; Golias, 2007). The main steps of the proposed ***MA*** are summarized in Figure 19 and explained in detail throughout this section.

In the first two steps, the chromosome and population are initialized. Then, the algorithm enters the main loop. In step 3, function ***SelectParents****(Pop(gen))* identifies parents in the population (i.e., variable *Parents(gen)*), while in step 4, function ***MAoperation****(Parents(gen))* applies stochastic operators and local search heuristics (***LSHs***) to produce the new offspring (i.e., variable (*Offsping(gen)*). The first group of ***LSHs*** is directed to improve the DCT vessel schedule (will be referred to as V_{DCT}) after applying the stochastic operator. The second group of ***LSHs*** is directed to improve the MUT vessel schedule (will be referred to as V_{MUT}) after applying the stochastic operator. In step 5, function ***Evaluate****(Offsping(gen))* calculates fitness values (i.e., variable *Fitness(gen)*) for the offspring, and in step 6, function ***Select****(Fitness(gen))* selects individuals, based on their fitness, to become parents in the next generation (step 7). ***MA*** exits the loop, when a termination criterion is satisfied. The algorithm was coded in MATLAB 7.11.0 (R2010b)[4]. Next the components of the developed ***MA*** are described in more detail.

[4] http://www.mathworks.com/

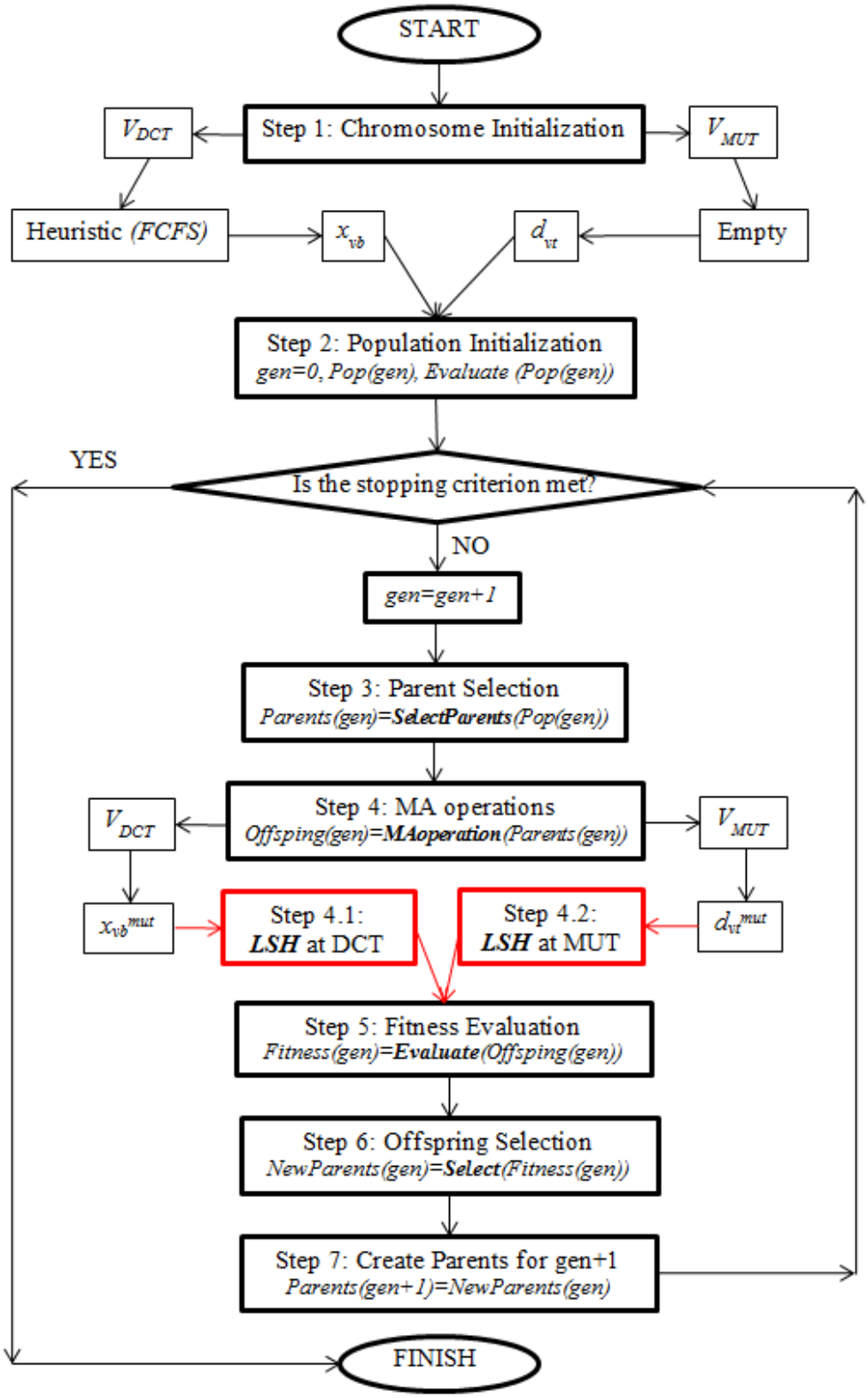


Figure 19. Solution Approach

Chromosome representation. An integer chromosome representation was adopted to represent a solution (i.e., individual or vessel assignment at both DCT and MUT). Note that terms of solution, individual, and vessel assignment will be used interchangeably throughout this chapter as they have the same meaning. Each chromosome is composed of genes (Eiben & Smith, 2003). Genes are represented by vessels, assigned for service at DCT and MUT. Position of a gene along the chromosome will be referred to as locus (Eiben & Smith, 2003). The value of each gene (i.e., vessel number or ID) will be referred to as allele (Eiben & Smith, 2003). An example of a chromosome for a small problem instance is shown in Figure 20, where six vessels request service at DCT, which has two berths. In this example MUT has six available TWs dedicated to serve the diverted vessels. It can be noticed that vessel "6" is diverted for service at MUT during the third TW. As for DCT, vessels "2", "4", and "5" are served (in that order) at berth "1", while vessels "1" and "3" are served (in that order) at berth "2".

Chromosome Representation																	
	The DCT												The MUT				
Vessel/Order	2	4	5	0	0	0	1	3	0	0	0	0	0	0	6	0	0
Berth/TW	Berth 1						Berth 2						1	2	3	4	5
													TWs				

Figure 20. Chromosome Representation Example

Population initialization. During initialization all vessels are assigned for service at DCT based on a First Come First Served with Earliest Finish Time Policy (***FCFS_EFTP***). If denote BA_b as the time when berth $b \in B$ becomes available; BP_b as the berthing position at berth $b \in B$; ST_v and FT_v as the start and finish service times of vessel $v \in V$, ***FCFS_EFTP*** can be described with the following pseudocode.

FCFS_EFTP Pseudocode

Set $BA_b = 0, BP_b = \emptyset \; \forall b \in B, ST_v = 0, FT_v = 0 \; \forall v \in V$
Sort vessels by their arrival times such that $A_{v-1} \leq A_v \; \forall v \in V$
for $\forall v \in V$
    $b = \underset{b}{argmin}(BA_b)$
    $BP_b \coloneqq BP_b \cup \{v\}$
    $ST_v = max(A_v, BA_b)$
    $FT_v = ST_v + S_{vb}$
    $BA_b = FT_v$
    $x_{vb} = 1$
end

Other heuristics or exact methods can be applied to initialize the chromosomes but are left as future research. Note that randomly initialized populations are not advisable, as they will contain a significant number of infeasible and low-quality individuals (Eiben & Smith, 2003; Sivanandam & Deepa, 2008). In this study various sizes of the initial population (*PopSize*) have been evaluated and details are presented in the numerical experiments section. The population size remains constant and equal to the initial population size throughout the ***MA*** operations.

Parent selection. Parent selection determines individuals from the current population that will be allowed to produce offspring via the ***MA*** operations at a given generation. The proposed ***MA*** applies a deterministic parent selection scheme (i.e., all survived offspring become parents) as this strategy is widely used in Evolutionary Programming and Genetic Algorithms (Eiben & Smith, 2003).

MA* operations.** Crossover and mutation are common ***EA*/*MA operators. However, for the chromosome structure, proposed in this study, typical crossover operators (e.g., one-point crossover, two-point crossover) will result in complex infeasibility, as each offspring may inherit combinations of parent genes, representing the same vessels. Such individuals may be also repaired. However, computational efforts will be much more significant as compared to repairing infeasibility, caused by mutation (as described in the next subsection). Several types of mutation operations have been presented in the literature (Eiben & Smith, 2003), and in this study swap mutation was applied due to its efficiency (Golias, 2007; Golias et al., 2010). Note that other mutation operators (e.g., insert, invert, scramble, etc.) were replaced by more efficient ***LSHs*** (described later in this section). The Swap Mutation Operator (SMO) randomly swaps genes along the chromosome, representing both groups of vessels served at DCT and MUT respectively (an example of swap mutation is shown in Figure 21 where vessels 5 and 6 swap terminals). The number of genes, swapped in each chromosome, is defined by the mutation rate (*MutRate*). Various *MutRate* values were tested during the ***MA*** evaluation and are presented in the numerical experiments section[5].

Before any further ***MA*** operations are performed, the Elitist strategy is employed to store the best individual and use as a parent in the next generation.

[5] Note that in this study *MutRate* is defined as the number of genes swapped in each chromosome.

Swap Mutation Operator

Before

	The DCT												The MUT				
Vessel/Order	2	4	5	0	0	0	1	3	0	0	0	0	0	6	0	0	0
Berth/TW	Berth 1						Berth 2						1	2	3	4	5
													TWs				

After

	The DCT												The MUT				
Vessel/Order	2	4	6	0	0	0	1	3	0	0	0	0	0	5	0	0	0
Berth/TW	Berth 1						Berth 2						1	2	3	4	5
													TWs				

Figure 21. Swap Mutation Operation Example

Feasibility during the *EA* evolution. A crucial feature of the ***MA*** design is to ensure feasibility of individuals at each generation. In the problem studied herein an individual may become infeasible, if service of a vessel, diverted to MUT, cannot be completed even under the highest available handling rate (at the assigned TW). In the proposed ***MA VHRE*** identifies vessels that cannot be diverted and passes this information to SMO (i.e., genes identified by ***VHRE*** will not be selected as swapping candidates). Another common strategy used to remedy infeasibility is penalty assignment (Eiben & Smith, 2003). However, low penalties may increase the probability of infeasible individuals' survival, and high penalties can negatively affect computational time, when probabilistic offspring selection schemes are applied (similar to the offspring selection scheme used in the proposed ***MA***, described in later in this section). The strategy of penalizing infeasible individuals was used only throughout refinement of the MUT vessel schedule to ensure that a vessel, assigned to a TW with sufficient duration to finish service will not be shifted to another smaller TW.

Figure 22 presents an example of another type of infeasible individuals that may be generated by SMO, where zero alleles between non-zero alleles are obtained. This type of infeasibility will cause bias, when estimating fitness function values of such individuals (loci colored in yellow). To address this issue the proposed ***MA*** includes an operator that repairs disrupted individuals (see Figure 22) by shifting zeros at each berth of the DCT and removes positional bias (see loci colored in green).

Infeasible Individual Possibly Generated by the Swap Operator

	The DCT												The MUT				
Vessel/Order	0	2	4	5	0	0	1	0	3	0	0	0	0	6	0	0	0
Berth/TW	Berth 1						Berth 2						1	2	3	4	5
													TWs				

Repairing Infeasible Individual

	The DCT												The MUT				
Vessel/Order	2	4	5	0	0	0	1	3	0	0	0	0	0	6	0	0	0
Berth/TW	Berth 1						Berth 2						1	2	3	4	5
													TWs				

Figure 22. Infeasible Individual Repairing Example

Local search heuristics (*LSHs*). In this section three ***LSHs***, developed to improve vessel assignment during ***MA*** operations, are described. Additionally, an optimization model is presented that is used to schedule vessels at MUT after SWO has been performed. Performance of the heuristics and the optimization model, in terms of computational time and solution quality, are evaluated in the numerical experiments section. As previously discussed, the heuristics and optimization model substitute genetic operations and are applied after the swap mutation operations (see Figure 23).

Dedicated container terminal local search heuristics.

Single Berth Dispatch Heuristic. The first DCT heuristic (from now referred as a Single Berth Dispatch Heuristic or ***SBDH***) belongs to the family of dispatch heuristics for the unrelated machine scheduling problem (Pinedo, 2008). Once jobs are assigned to each machine, dispatch heuristics are applied to refine the initial schedule based on attributes of each job (e.g., assigning jobs of the same family in a batch requires a machine set up only for the first job, which will reduce the total set up costs). ***SBDH*** estimates the vessel service order at each berth (without considering vessels at the other berths) and is based on two parameters: arrival ($A_v \; \forall v \in V_{DCT}$) and handling times ($S_{vb} = \frac{NC_v}{D_b} \; \forall v \in V_{DCT}, b \in B$). Depending on the average arrival and handling times, ***SBDH*** sorts DCT vessels either based on their arrival or handling time, or based on the sum of their arrival and handling times.

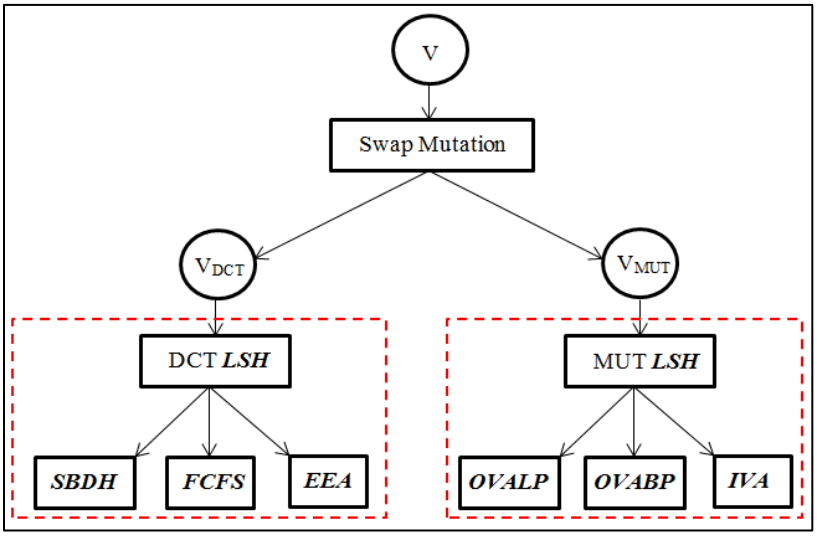


Figure 23. Local Search Heuristics

In case of a static berth allocation problem, where all vessels are already at the port in the beginning of the planning horizon, vessels are sorted only based on their handling times. Note that hours of early and late departures (i.e., components of the objective function) are dependent on the departure time request of each vessel: $LD_v = f(RD_v), ED_v = f(RD_v)$. In this study the requested departure time of each vessel was assigned based on the vessels' arrival and handling times (i.e., $RD_v = f(A_v, S_{vb})\ \forall v \in V_{DCT}, b \in B$). Hence, both ***SBDH*** attributes directly account for the problem objective. The steps of ***SBDH*** can be described by the following pseudocode.

SBDH Pseudocode

for $\forall b \in B$ refine the vessel service order
    if $TI_b < min(A_v)$ & $[mean\ (A_v) - min(A_v)] > mean\ (S_{vb}) + TH$
    Sort vessels based on A_v
    elseif $TI_b < min(A_v)$ & $[mean\ (A_v) - min(A_v)] + TH < mean\ (S_{vb})$
    Sort vessels based on S_{vb}
    elseif $TI_b < min(A_v)$ & $|[mean\ (A_v) - min(A_v)] - mean\ (S_{vb})| \leq TH$
    Sort vessels based on $A_v + S_{vb}$
    elseif $TI_b \geq max(A_v)$
    Sort vessels based on S_{vb}
    end
end

Note TI_b – time when the berth $b \in B$ becomes idle at the first time in the planning horizon (in this study $TI_b = 0\ \forall b \in B$);
TH – pre-specified threshold value.

A sensitivity analysis for the threshold value TH was conducted and presented in the numerical experiments section.

First Come First Served Heuristic. FCFS_EFTP, presented earlier in this section, is also used to improve vessel assignment at DCT. The only difference is that it is applied only to the vessels assigned for service at DCT ($v \in V_{DCT}$). To differentiate it will be referred to as ***FCFS***.

Epochal EA. The third heuristic (referred to as Epochal EA or ***EEA***) employs an ***EA*** at each DCT berth (from now on referred to as Single Berth ***EA*** or ***SBEA***) to improve vessel assignment. Chromosome representation for ***SBEA*** is depicted in Figure 24A, where six vessels "2", "5", "4", "7", "9", and "8" (in that order) request service at berth $b \in B$ of DCT. ***SBEA*** has features similar to ***MA***: a) deterministic parent selection, b) swap mutation for the ***EA*** operations (see Figure 24B), and c) offspring selection (discussed later in this section).

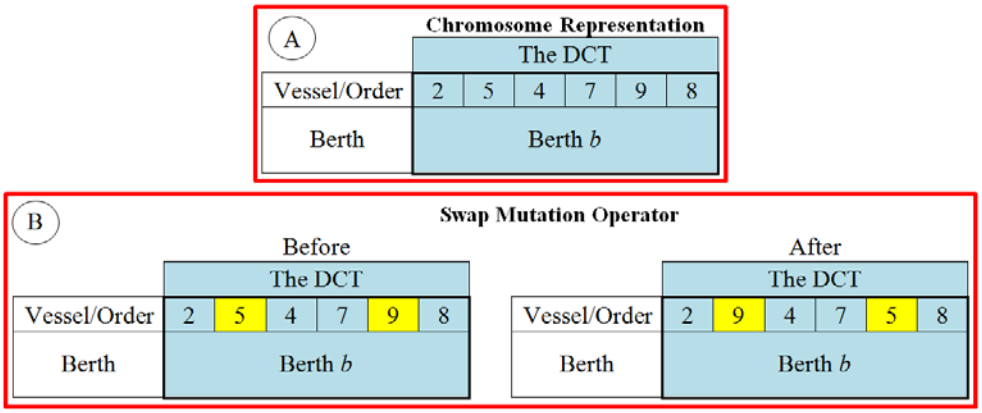


Figure 24. ***SBEA*** Features

The main drawback of using an additional ***EA*** within ***MA*** is an increase in time complexity. To address this issue ***SBEA*** is applied periodically and only after a pre-specified number of generations (a.k.a. epoch[6]), and only on a group of individuals within the population, not the whole population.

[6] The notion of "epoch" is widely used in Island ***EA*** models (Eiben & Smith, 2003).

Multi-user terminal vessel assignment. A mathematical model was developed to assign diverted vessels to the available TWs at MUT during each generation. The model formulation (which is a relaxation of ***BSDM*** and referred to as ***P1***) is as follows.

$$\boldsymbol{P1:}\ min[\sum_{v\in V_{MUT}}\sum_{t\in T}(NC_v d_{vt} hc_t^r\ ) + \sum_{v\in V_{MUT}}(dc_v LD_v) - \sum_{v\in V_{MUT}}(ep_v ED_v)] \tag{24}$$

Subject to:

(8), (9), (10), (13), (14), (16), (17), (19), (20), (23)

$$\sum_{t\in T} d_{vt}\ = 1\ \forall v \in V_{MUT} \tag{25}$$

$$\sum_{v\in V_{MUT}} d_{vt}\ \leq 1\ \forall t \in T \tag{26}$$

The objective function (24) minimizes the overall service cost of diverted vessels, i.e., handling costs, penalties due to late vessel departures, and premiums due to early vessel departures. Constraints set (25) ensure that each diverted vessel is served only once. Constraints set (26) indicate that no more than one diverted vessel can be served at each TW. ***P1*** includes one decision variable ($d_{vt}\ \forall v \in V_{MUT}, t \in T$), several auxiliary variables (i.e., $t_v, LD_v, ED_v\ \forall v \in V_{MUT}$) and non-linear constraints set (16). Note that the total service costs of all potentially diverted vessels during each TW under the optimal handling rate are estimated by ***VHRE***. Hence, ***P1*** can be reduced to a less complex problem, where service costs at MUT for a given set of diverted vessels are already known. Thus, ***P1*** can be reformulated as follows.

$$\boldsymbol{P2:}\ \min \sum_{v\in V_{MUT}}\sum_{t\in T} c_{vt} d_{vt} \tag{27}$$

Subject to:

(19), (25), (26)

where c_{vt} is the total cost of vessel service during a TW at MUT, estimated by ***VHRE.***

Even though ***P2*** is unimodular (Rader, 2010) the solution time complexity depends on the software used. In this study three solution approaches were evaluated to solve ***P2***: a) A binary formulation using MATLAB's optimization solver (this solution approach will be referred to as ***OVABP***[7]), b) A linear relaxation of ***P2*** (i.e., relax integrality constraints) using GAMS[8] optimization solver (this solution approach will be referred to as ***OVALP***), and c) A heuristic solution algorithm (this solution approach will be referred to as ***IVA***[9]). GAMS was used as a solver for the second approach due to the inability of MATLAB linear optimization solver to produce an integer solution. Next ***IVA*** is described in more detail.

IVA heuristic. Let $V_{MUT} = \{1,2,\dots,v\}$ and $T = \{1,2,\dots,t\}$ be the set of vessels, diverted for service at MUT, and available TWs respectively. Also let t_v be a TW, to which vessel v is assigned for service. For each diverted vessel at MUT the total cost (c_{vt}) is calculated for each TW, associated with service of a given vessel. If a vessel cannot finish service at TW, then that cost is set equal to a large positive number *M*. Let $C_{vt} = min_{t\in T}(c_{vt})\ \forall v \in V_{MUT}$ be the minimum service cost of vessel v during TW *t*. Priority of a vessel to occupy a TW is defined as the sum of additional costs, endured by the vessel, if it is not served at the TW with the minimum cost: $p_v = \sum_{t\in T}(c_{vt} - C_{vt})\ \forall v \in V_{MUT}$.

Once these inputs are calculated, ***IVA*** selects the vessel with the highest priority and assigns it to the TW with the minimum cost. That vessel and the TW, it occupies, are

[7] Abbreviation OVA denotes "optimal vessel assignment", BP and LP stand for binary and linear programming respectively

[8] http://www.gams.com/

[9] Abbreviation IVA denotes "improved vessel assignment"

removed from the list of vessels (V_{MUT}) and available TWs (T) respectively, and priorities for the remainder of the vessels are recalculated. The procedure continues until each vessel has been assigned to a TW. The ***IVA*** pseudocode is presented next.

IVA Pseudocode

while $V_{MUT} \neq \emptyset$

$$C_{vt} = \min_{t \in T}(c_{vt}) \ \forall v \in V_{MUT}$$

$$p_v = \sum_{t \in T}(c_{vt} - C_{vt}) \ \forall v \in V_{MUT}$$

$$v = \underset{v}{argmax}(p_v)$$

$$t_v = \underset{t}{argmin}(c_{vt})$$

$$V_{MUT} \coloneqq V_{MUT} - \{v\}$$

$$T \coloneqq T - \{t\}$$

end

The time complexity of the three proposed solution approaches for the ***P2*** and optimality gap analysis for ***IVA*** will be performed during numerical experiments.

Fitness function. For ***EAs***/***MAs*** the fitness function is usually associated with the objective function (Sivanandam & Deepa, 2008). In the proposed ***MA*** the fitness function value was set equal to the objective function value without applying any scaling mechanisms.

Offspring selection. Offspring selection at a given generation of a ***MA*** is an important part of its design. It allows choosing the strongest individuals that will be able to adapt to the environment and reproduce competent parents, while at the same time allowing for a small number of weak individuals to move on (Sivanandam & Deepa, 2008). In this study a selection procedure similar to the Roulette Wheel Selection or ***RWS*** (Goldberg, 1989) was developed.

Probabilistic selection mechanisms (like ***RWS***) do not necessarily keep the best individuals and do not necessarily exclude the worst individuals, resulting in a genetic drift (Eiben & Smith, 2003). To address the first issue (i.e., keep the best individuals) the Elitist Strategy is applied. To address the second issue (i.e., excluding the worst individuals and avoiding genetic drift) a Modified ***RWS*** (***MRWS***) is designed and outlined next.

MRWS Pseudocode

Step 1: Calculate normalized fitness values for each individual
Step 2: Sort mutated individuals by normalized fitness values in the ascending order
Step 3: Estimate cumulative fitness values
Step 4: Flip the coin and get the value between 0 and *SelectPar* ("rotate the wheel")
Step 5: Identify the individual with cumulative fitness value, close to the one obtained from Step 4. Select this individual for the next generation
Step 6: Repeat Steps 4 and 5 until the desired population size is reached

The main difference between ***RWS*** and ***MRWS*** is that mutated individuals are sorted by normalized fitness values in the ascending order, and an additional parameter *SelectPar* (with values between 0 and 1) is introduced to define the "wheel's rotation". Depending on the search objectives *SelectPar* values may vary (high for exploration and low for exploitation). Based on preliminary ***MA*** runs *SelectPar* =0.20 was found to be efficient (i.e., demonstrated faster convergence and lower objective function values). Lower values of *SelectPar* are not recommended, as they may potentially result in premature convergence. ***MRWS*** was validated against the Tournament Selection mechanism, and provided better solution quality and faster convergence.

Stopping criterion. If the optimal objective function value or a lower bound is known a priori, the algorithm can be stopped once a specified optimality gap is reached. ***BSDM*** is NP-hard, and the optimal solution (or a strict lower bound) is not known in advance. In this study the algorithm was terminated, if no change in the objective function value occurred after a pre-specified number of generations (*MaxNumGen* of 3000 generations) or the maximum number of generations is reached (*LimitGen* of 10000 generations).

Numerical Experiments

This section presents numerical experiments that were performed to evaluate the proposed ***MA*** and to assess benefits from the suggested berthing policy. Numerical data used (shown in Table 7) were generated based on the available port operations literature (Ballis, Dimitriou & Paravantis, 2010; Carlo et al., 2013; Golias, 2007, etc.). Three vessel interarrival time (IAT) patterns of 2, 3, and 4 hours were considered to evaluate the proposed berth scheduling policy under high, medium, and low demand respectively.

Vessel interarrival times were assumed to follow the exponential distribution. Based on the available literature (Trade Fact of the Week, 2014; TRP, 2014) and assuming a mix of vessel operations that include mooring, loading and discharge of containers, type of container (empty, loaded, size, reefer), re-stowing (on-board the vessel or via quay), the DCT handling cost was set equal to $650 per container.

Table 7
Numerical Data

Planning horizon	1 week
Vessel interarrival patterns (exponential)	2, 3, and 4 hrs.
Requested vessel departure $[RD_v\ \forall v \in V]$	Arrival time + Handling Time × [U(1.0-1.2)[10], U(1.2-1.4), U(1.4-1.6), U(1.6-1.8)]
Containers assigned to each vessel $[NC_v\ \forall v \in V]$	U(750-3000) TEUs
Handling rate at DCT preferred berth $[D_{vb}\ \forall v \in V, b \in B]$	125 TEUs/hr.
DCT number of berths	4, 6, 8
MUT number of available TWs	0, 5, 10, 15, 20
TW duration	10÷20 hrs.
MUT available handling rates $[r \in R_t]$	[75; 125; 150; 250] TEUs/hr.
Charge at MUT $[hc_t^{rt}\ \forall t \in T, t \in R_t]$	[750; 1000; 1200; 2000] USD/TEU
Late departure penalty $[dc_v\ \forall v \in V]$	7000 USD/hr.
Early departure premium $[ep_v\ \forall v \in V]$	5000 USD/hr. (70% of the penalty)

The DCT handling rate at the "preferred berth" was set equal to 125 TEUs/hr. (e.g., five QCs with average productivity of 25 TEUs/hrs. are assigned to each berth). The "preferred berth" was identified for each vessel based on ***FCFS_EFTP*** (assuming at this stage that all berths are preferred berths). The handling time of vessels at the other berths was generated in relation to the berth with the minimum handling time. Handling charges at MUT, as previously discussed, were dependent on the handling rate requested, and were assumed to be higher than the handling charges at DCT (Ballis et al., 2010). The range of MUT handling rates was selected based on the data, published in the Journal of Commerce for 2012-13 (Journal of Commerce, 2014). It was assumed that the MUT operator can provide 4 different handling rates for each TW. The number of available TWs varied from zero (the DCT operator cannot divert any vessels to MUT) to 20. Hourly late/early departure penalties/premiums were also based on the available literature

[10] *U(a,b)* refers to uniformly distributed pseudorandom numbers between *a* and *b*

(Zampelli et al., 2013). Various vessel departure requests were considered and were dependent on the vessels' arrival time.

Using the data presented in Table 7 two subsets of datasets were developed. The first subset of datasets was used for the evaluation of the berth scheduling policy and consisted of 180 instances of all possible combinations of vessel arrivals, vessel departure requests, DCT berth configurations, and TW availability shown in Table 7 (i.e., [3 vessel arrivals] × [4 vessel departure requests] × [3 DCT berth configurations] × [5 TW availabilities at MUT]). The second subset of datasets was used for the evaluation of MA and LSHs and sensitivity analysis of their parameters. Each instance of the second subset will be described in the latter sections. The rational of using two different groups of datasets is to avoid bias in the evaluation of the berth scheduling policy (i.e., evaluate the berthing policy with datasets that were used to select the MA parameters and LSHs). All numerical experiments were conducted on a Dell T1500 Intel(T) Core i5 Processor with 1.96 GB of RAM.

MA* parameter tuning.** Population size (*PopSize)* and mutation rate (*MutRate)* were selected based on preliminary ***MA runs. Four instances were used during this analysis. Each instance had the following common characteristics: a) 4 DCT berths, b) high demand (IAT = 2 hrs.), and c) 20 TWs. Instances differed by the requested vessel departure times: a) Instance 1: $RD_v = A_v + \mathrm{S}_{vb} \times U(1.0 - 1.2)$ – referred to as RD1, b) Instance 2: $RD_v = A_v + \mathrm{S}_{vb} \times U(1.2 - 1.4)$ – referred to as RD2, c) Instance 3: $RD_v = A_v + \mathrm{S}_{vb} \times U(1.4 - 1.6)$ – referred to as RD3, and d) Instance 4: $RD_v = A_v + \mathrm{S}_{vb} \times U(1.6 - 1.8)$ – referred to as RD4.

Three different *MutRate* values (*MutRate* = {2, 4, 6}) were evaluated using *MA* with *PopSize* = 40, *MaxNumGen* = 3000, *LimitGen* = 10000, and *SelectPar* = 0.20. Similarly, five *PopSize* values were evaluated (*PopSize* = {20, 30, 40, 50, 60}) using *MA* with *MutRate* = 2, *MaxNumGen* = 3000, *LimitGen* = 10000, and *SelectPar* = 0.20. *LSHs* were not used during the *MA* parameter selection, as they will be implemented as auxiliary means of improving solution quality after applying SWO.

Ten ***MA*** replications were performed for each instance, and the average objective function and computational time values are presented in Figures 25 and 26. These results indicate that *PopSize* of 30 and *MutRate* of 2 demonstrated the best trade-off between the solution quality and the computational time.

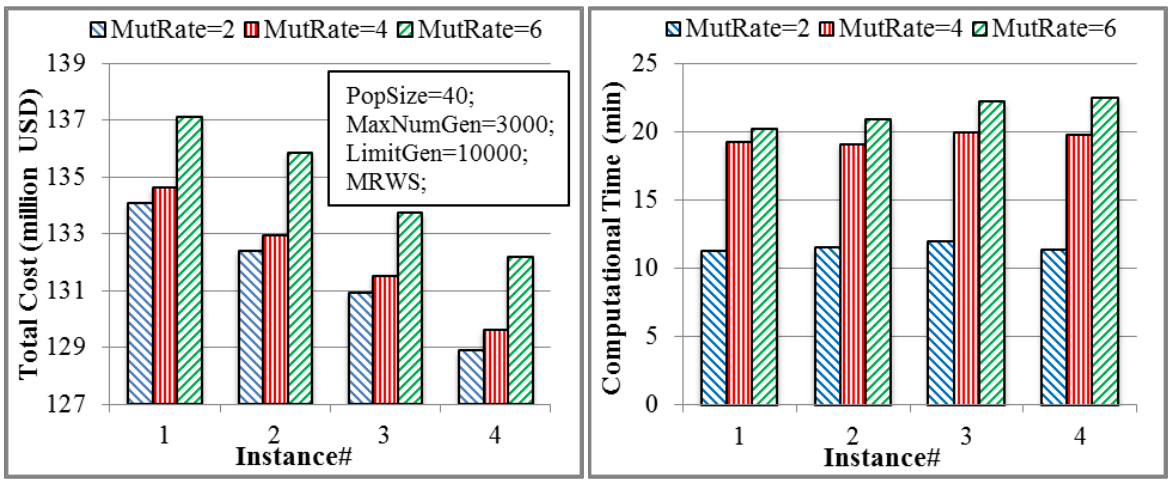


Figure 25. Mutation Rate Sensitivity Analysis

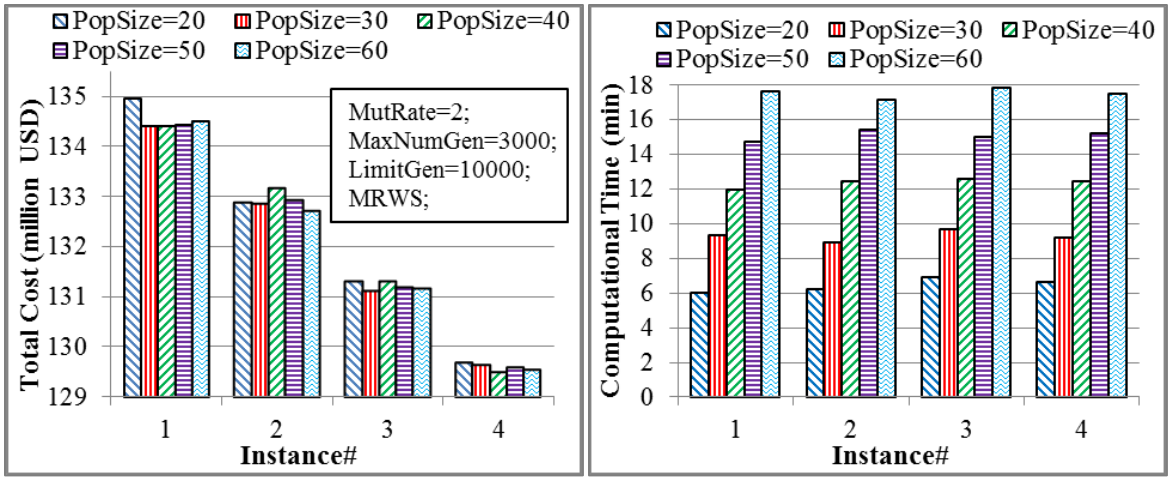


Figure 26. Population Size Sensitivity Analysis

Evaluation of *LSHs* at DCT

SBDH sensitivity analysis. The main objective of ***SBDH*** sensitivity analysis was to determine the TH value. A total of seven TH values were evaluated: $TH = \{0, 5, 10, 15, 20, 30, 40\}$. For each TH value 33 instances were developed with each instance having a different vessel IAT (2, 3, and 4 hours) and number of vessels served (ranging from 10 to 30 with an increment of two). For each instance 500 cases were generated with vessel demand varying uniformly between 750 and 3000 TEUs, and RD1 as the requested departure time for each vessel. Since ***SBDH*** is a heuristic, five replications of ***SBDH*** for each case were performed, and the average objective function value (i.e., DCT vessel service costs) for each instance over 500 cases and five replications are reported in Table 8.

It can be observed that increasing TH values (e.g., $TH = 40$) reduces the service cost for instances with frequent vessel arrivals (e.g., IAT = 2) and higher number of vessels. However, cost savings do not exceed ≈3% for instances with high demand, while no substantial difference in the objective function values was observed for instances with low demand. Thus, ***SBDH*** threshold value $TH = 40$ will be used in this study. As a

result of this analysis, it was found that *TH* value did not affect the computational time of ***MA-SBDH*** (i.e., ***MA*** that applies ***SBDH*** as ***LSH*** at DCT).

Table 8
SBDH *Threshold Sensitivity Analysis*

		DCT Vessel Service Cost (million USD)										
		Vessels										
IAT	TH	10	12	14	16	18	20	22	24	26	28	30
2	0	16.04	20.05	24.96	30.07	35.45	41.47	47.66	54.23	61.15	68.67	75.88
	5	15.93	19.85	24.66	29.73	34.98	41.00	47.12	53.64	60.76	68.40	75.71
	10	15.85	19.79	24.60	29.68	34.83	40.67	46.66	53.12	60.17	67.80	75.13
	15	15.84	19.79	24.60	29.66	34.79	40.59	46.52	52.83	59.74	67.21	74.44
	20	15.84	19.79	24.59	29.66	34.79	40.57	46.47	52.73	59.55	66.91	73.98
	30	15.84	19.79	24.59	29.66	34.79	40.57	46.46	52.69	59.48	66.79	73.77
	40	15.84	19.79	24.59	29.66	34.79	40.57	46.46	52.69	59.48	66.78	73.75
3	0	15.97	20.15	24.73	29.25	34.80	40.47	46.09	52.63	59.11	65.90	73.62
	5	15.76	19.90	24.45	29.02	34.63	40.37	46.00	52.61	59.10	65.88	73.62
	10	15.72	19.86	24.34	28.86	34.42	40.17	45.85	52.43	59.00	65.83	73.60
	15	15.71	19.84	24.29	28.76	34.24	39.95	45.63	52.22	58.83	65.71	73.51
	20	15.71	19.84	24.28	28.72	34.16	39.82	45.40	51.96	58.57	65.45	73.31
	30	15.71	19.84	24.27	28.69	34.11	39.73	45.22	51.68	58.15	64.95	72.71
	40	15.71	19.84	24.27	28.69	34.11	39.72	45.19	51.62	58.00	64.73	72.36
4	0	15.72	19.64	24.13	28.79	34.09	39.12	45.04	50.61	57.21	63.47	69.81
	5	15.53	19.51	23.98	28.73	34.03	39.09	45.04	50.60	57.21	63.47	69.81
	10	15.47	19.43	23.88	28.63	33.94	39.04	45.00	50.59	57.20	63.47	69.81
	15	15.46	19.40	23.81	28.52	33.79	38.96	44.93	50.54	57.19	63.44	69.80
	20	15.45	19.38	23.79	28.44	33.69	38.83	44.80	50.46	57.14	63.41	69.80
	30	15.45	19.37	23.76	28.36	33.57	38.65	44.54	50.18	56.87	63.19	69.67
	40	15.45	19.37	23.75	28.35	33.54	38.58	44.40	50.01	56.61	62.91	69.36

EEA sensitivity analysis. Two sensitivity analyses were conducted to select *Epoch* value for ***MA*** that applies ***EEA*** (from now on referred to as ***MA-EEA***) and to determine ***SBEA*** population size *PopSizeSBEA* that provides high quality individuals within acceptable computational time. Four instances and the ***MA*** parameters, presented in the ***MA*** parameter tuning section, were used during these experiments with *Epoch* values of 30, 50, 100, 150, and 200.

For ***SBEA*** *PopSizeSBEA* = 10, *MutRateSBEA* = 2, *MaxNumGenSBEA* = 100, and *SelectParSBEA* = 0.20 were used. The quantity of individuals ($q \in Q$), chosen for improvement by ***EEA***, was uniformly distributed between 10% and 20% of the ***MA*** population. The average objective function and computational time values over ten replications of ***MA-EEA*** are presented in Figure 27. As expected, ***SBEA*** is used more often for refining DCT vessel assignment in cases with low *Epoch* values, which improves the objective function value at termination, but increases the computational time. The best trade-off between the objective function value and the computational time was obtained for *Epoch* = 100. Decreasing *Epoch* substantially increased the ***MA*** time complexity (e.g., increase by ≈7.9 min and 17.4 min on average for ***EEA*** with *Epoch* = 50 and 30 respectively, as compared to ***EEA*** with *Epoch* = 100) without significant reduction in the objective function value.

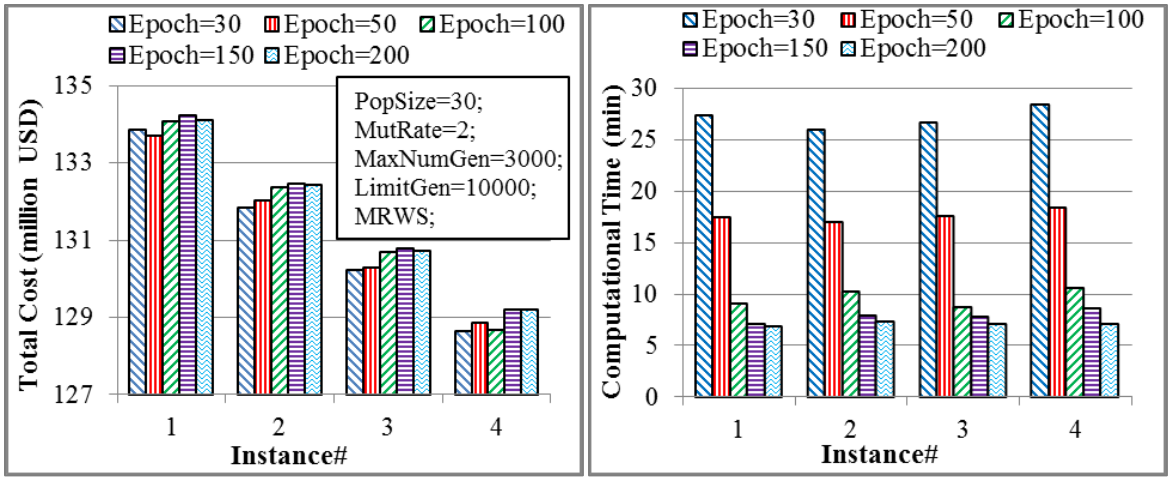


Figure 27. Epoch Sensitivity Analysis

The second sensitivity analysis evaluated performance of ***SBEA*** with *MutRateSBEA* = 2, *MaxNumGenSBEA* = 100, and *SelectParSBEA* = 0.20 for different *PopSizeSBEA* of 5, 10, 15, and 20, using the same parameters for ***MA-EEA*** as for the first sensitivity analysis. The average objective function and computational time values over 10 replications of ***MA-EEA*** are depicted in Figure 28. A *PopSizeSBEA* of 10 demonstrated the best trade-off between the objective function value at termination and the computational time. Increasing population size increased time complexity of the algorithm (e.g., increase by ≈2.8 min and 5.9 min on average for ***SBEA*** with *PopSizeSBEA* of 15 and 20 respectively, as compared to ***SBEA*** with *PopSizeSBEA* of 10) without significant reduction in the total cost. Hence, *PopSizeSBEA* of 10 will be used for ***SBEA***.

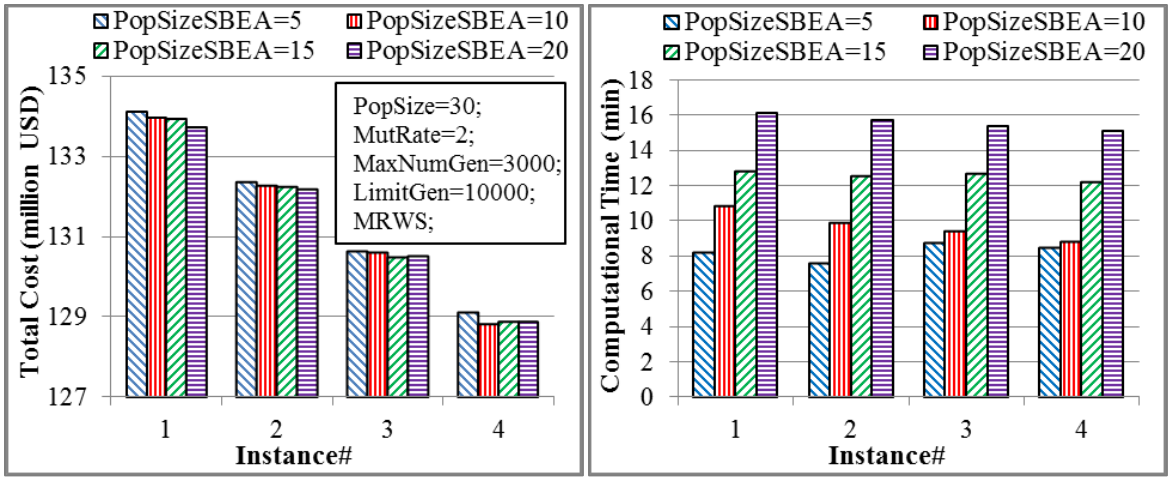


Figure 28. ***SBEA*** Population Size Sensitivity Analysis

LSH* evaluation at MUT.** A time complexity analysis was conducted for the three solution approaches (OVALP***, ***OVABP***, and ***IVA***). Twenty instances with different TWs, ranging from 2 to 40 with an increment of two, were developed. For each instance 500 cases were created with different number of containers per vessel, uniformly distributed between 750 and 3000 TEUs. It was assumed that the number of diverted vessels was equal to the number of available TWs (i.e., the worst complexity for the MUT scheduling that may occur during the ***MA*** evolution), and IAT was equal to 2 hours. TW duration varied uniformly between 20 and 30 hours. The requested departure time RD1 was assumed for each vessel. The rest of parameters were adopted from Table 7. Five replications of each solution approach were performed for each case to estimate the average computational time (objective function values did not change from replication to replication). Results of the time complexity analysis for ***OVALP***, ***OVABP***, and ***IVA*** are presented in Figure 29 for each one of the 20 instances (average values over 500 cases and 5 replications for each instance).

IVA substantially outperformed ***OVALP*** and ***OVABP*** in terms of computational time (e.g., 0.006 sec vs. 0.265 sec vs. 1.010 sec respectively for TWs = 40). ***OVABP*** was more efficient than ***OVALP*** for scenarios with TWs < 20. This can be explained by ***OVALP*** requiring additional time for exchanging data between MATLAB and the external optimization solver (GAMS). However, when the number of available TWs at MUT exceeds 20, ***OVALP*** is recommended to determine the optimal MUT vessel assignment.

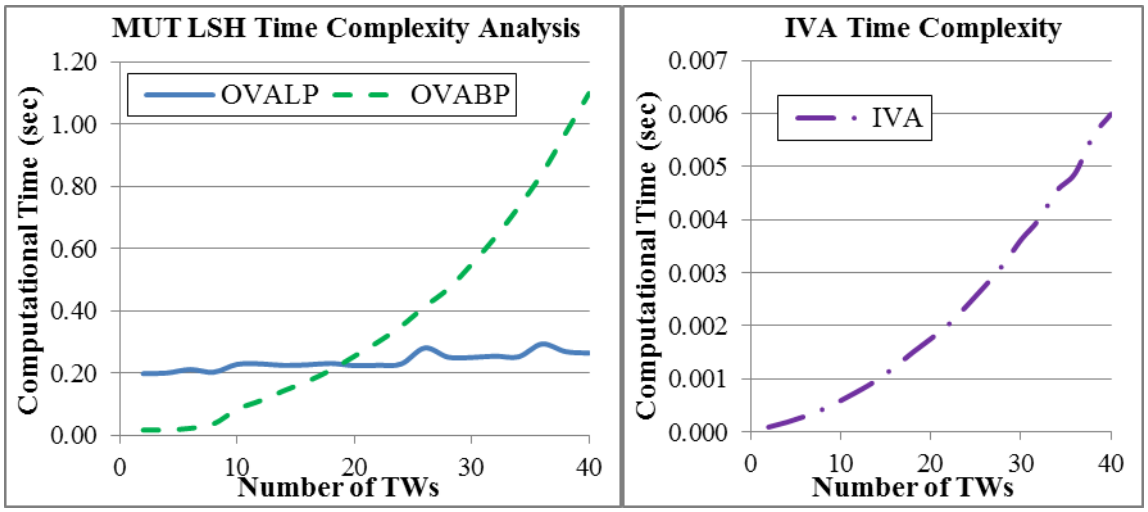


Figure 29. MUT ***LSH*** Time Complexity Analysis

IVA optimality gap was also estimated, and Figure 30 illustrates boxplots with optimality gap values for 500 cases of each instance. It can be observed that the optimality gap Δ does not exceed 7% over all cases and instances. The maximum average optimality gap $\Delta = 3.73\%$ was observed for instance with 40 TWs. Based on ***IVA*** time complexity and optimality gap analysis, the heuristic was found to be applicable as the least time consuming with acceptable optimality gaps.

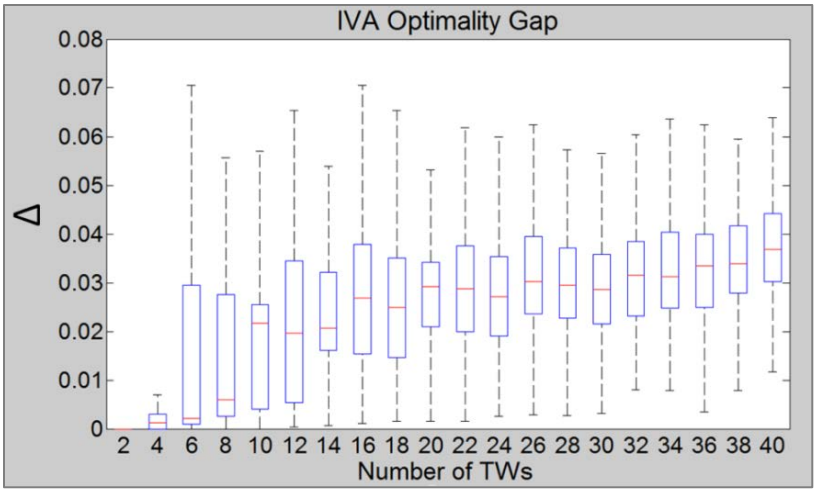


Figure 30. ***IVA*** Optimality Gap

MA* performance.** The next step in the analysis was to evaluate performance of the proposed solution algorithm that replaces common mutation operations with ***LSHs. Three different combinations were compared following the naming convention: ***MA-LSH-IVA*** (i.e., ***MA*** that applies ***LSH*** at DCT and ***IVA*** at MUT). The first combination (***MA-SBDH-IVA***) applied ***SBDH***, the second ***FCFS*** and the third ***EEA*** to improve vessel scheduling at DCT after SWO. All three combinations used ***IVA*** to improve vessel scheduling at MUT after SWO (i.e., as the solution approach for ***P2***). Note that ***OVABP*** is still applied after convergence to the best individual to ensure optimality of the final MUT vessel assignment. Four instances, used for the ***MA*** parameter tuning, were adopted during these experiments. Convergence patterns of the three ***MAs*** and the objective function values at termination (for the replications with the minimum total cost) are presented in Figure 31.

MA-EEA-IVA outperforms the other two combinations in terms of the solution quality. Introduction of ***OVABP*** for the best individuals was crucial, as it provided cost reduction after termination for the majority of cases (a cost reduction is denoted by the

red circle at the last generation). The objective function value, obtained by ***MA-EEA-IVA***, was on average 2.8% and 8.2% lower as compared to ***MA-SBDH-IVA*** and ***MA-FCFS-IVA*** respectively. However, ***MA-EEA-IVA*** computational time (16.3 minutes) was on average 31% and 51% higher as compared to ***MA-SBDH-IVA*** and ***MA-FCFS-IVA*** respectively (Figure 32). Nevertheless, ***MA-EEA-IVA*** was selected as the solution algorithm for the evaluation of the berthing policy as it provided the lowest objective function value for all instances within acceptable computational time.

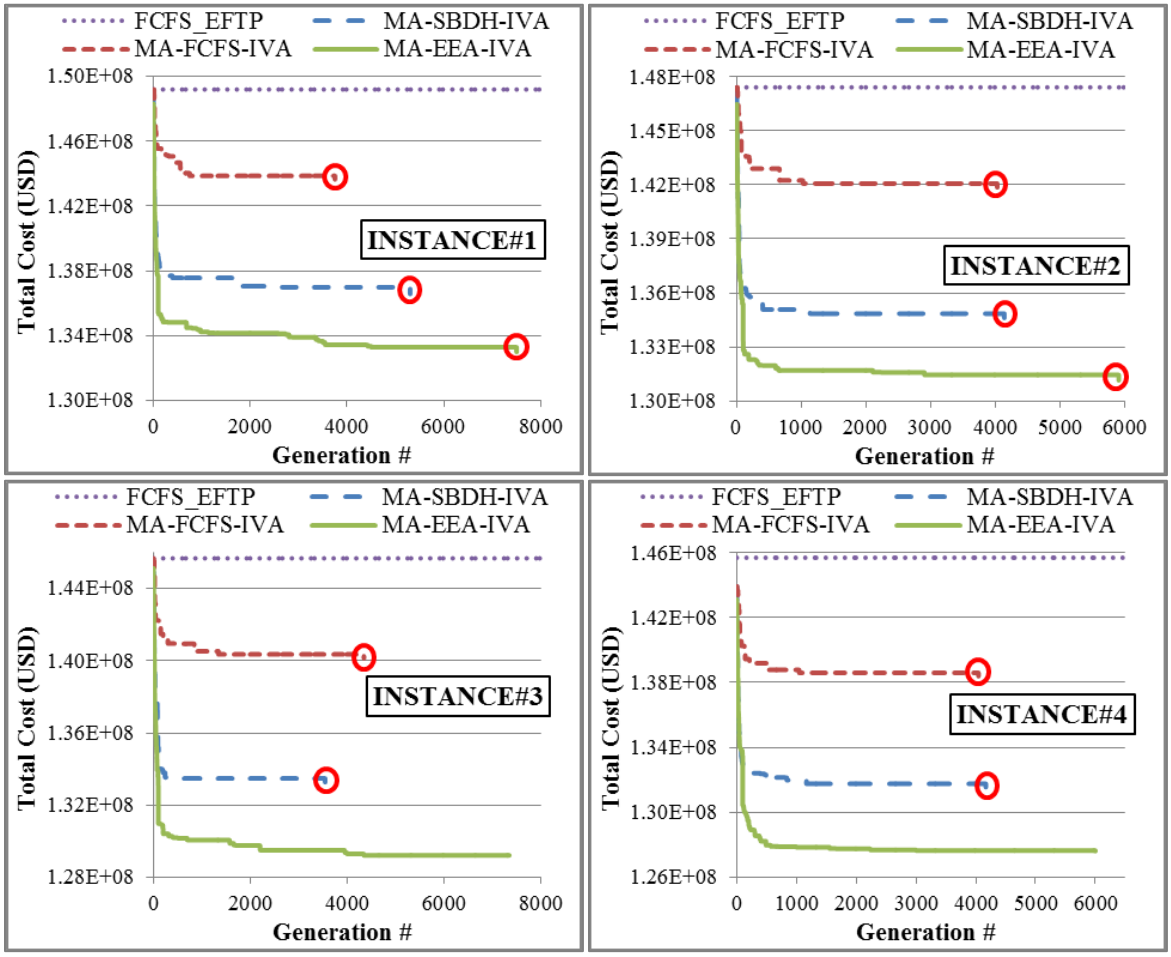


Figure 31. Convergence Patterns of ***MA*** with Various DCT and MUT ***LSHs***

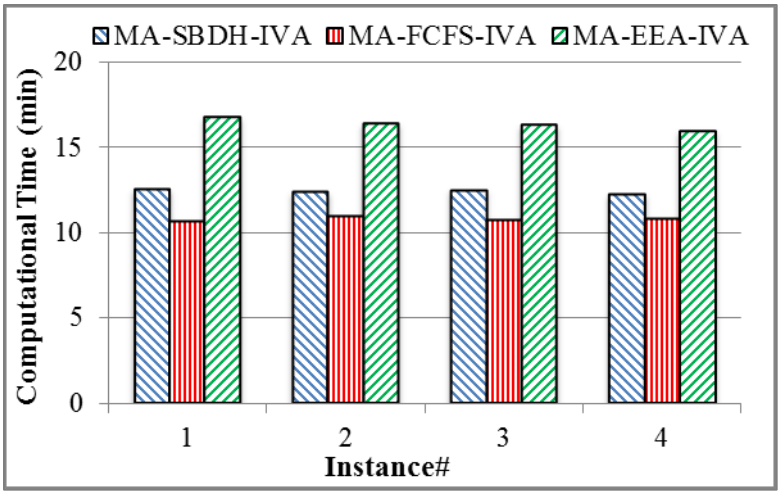


Figure 32. Computational Time of ***MA*** with Various ***LSHs***

Berthing policy evaluation. Three performance measures were chosen to quantify benefits from the suggested berth scheduling policy: i) cost savings per TEU, ii) total savings over the planning horizon (i.e., 1 week), and iii) TW utilization (i.e., how many vessels were diverted to MUT). All 180 instances described in the beginning of this section were used as input data. Next findings for each one of the three performance measures are presented.

Cost per TEU. Costs per TEU are presented in Figure 33, where the x-axis of each graph has two components: a) the number of available TWs at MUT, and b) arrival pattern of vessels. The upper right corner of each chart denotes the number of berths available at DCT. For example, the utmost left group of bars at the top chart (see Figure 33) indicates that if there are no available TWs at MUT (TWs = 0) during high demand period (IAT = 2 hrs.), and DCT has 4 berths, the DCT operator has to charge (in order to be profitable) the liner shipping company at least $856, $844, $832, and $821 for service of vessels, for requested departure times RD1, RD2, RD3, and RD4 respectively.

The latter finding was expected as the total service costs should decrease with less strict vessel departure requests. Cost per TEU reduced with increasing number of TWs for instances with frequent vessel arrivals (i.e., high demand period) and lower DCT capacity (e.g., DCT configuration with 4 berths). No substantial changes were observed during low demand periods (e.g., IAT = 4 hrs.) and high berth capacity at the DCT (e.g., 8 berths). In certain instances costs per TEU were lower that the DCT handling cost of $650 (e.g., $622 for DCT with 6 berths IAT = 4 hrs., TWs=0÷20, and RD4). This can be explained by the fact that ***MA-EEA-IVA*** provided an efficient vessel assignment, when additional savings incurred due to early vessel departures.

Total savings. Total savings were estimated as the difference in the objective function value for the case when all vessels were handled at DCT (i.e., TWs = 0), and the cases when a subset of vessels were diverted for service at MUT (i.e., TWs > 0). Results of the analysis are presented in Figure 34, where the x-axis of each graph has two components: a) the number of available TWs at MUT, and b) arrival pattern of vessels. The upper right corner of each chart denotes the number of berths available at DCT. For example, the second from the left group of bars at the top chart (see Figure 34) indicates that for the case of five available TWs at MUT (TWs = 5), high demand period (IAT = 2 hrs.), and 4 DCT berths, monetary benefits (for the DCT operator) from diverting vessels to MUT range from $1.25 to $1.57 million. Note that no significant savings were observed for low demand periods (e.g., IAT = 4 hrs.) and high DCT berth capacity (e.g., 8 berths).

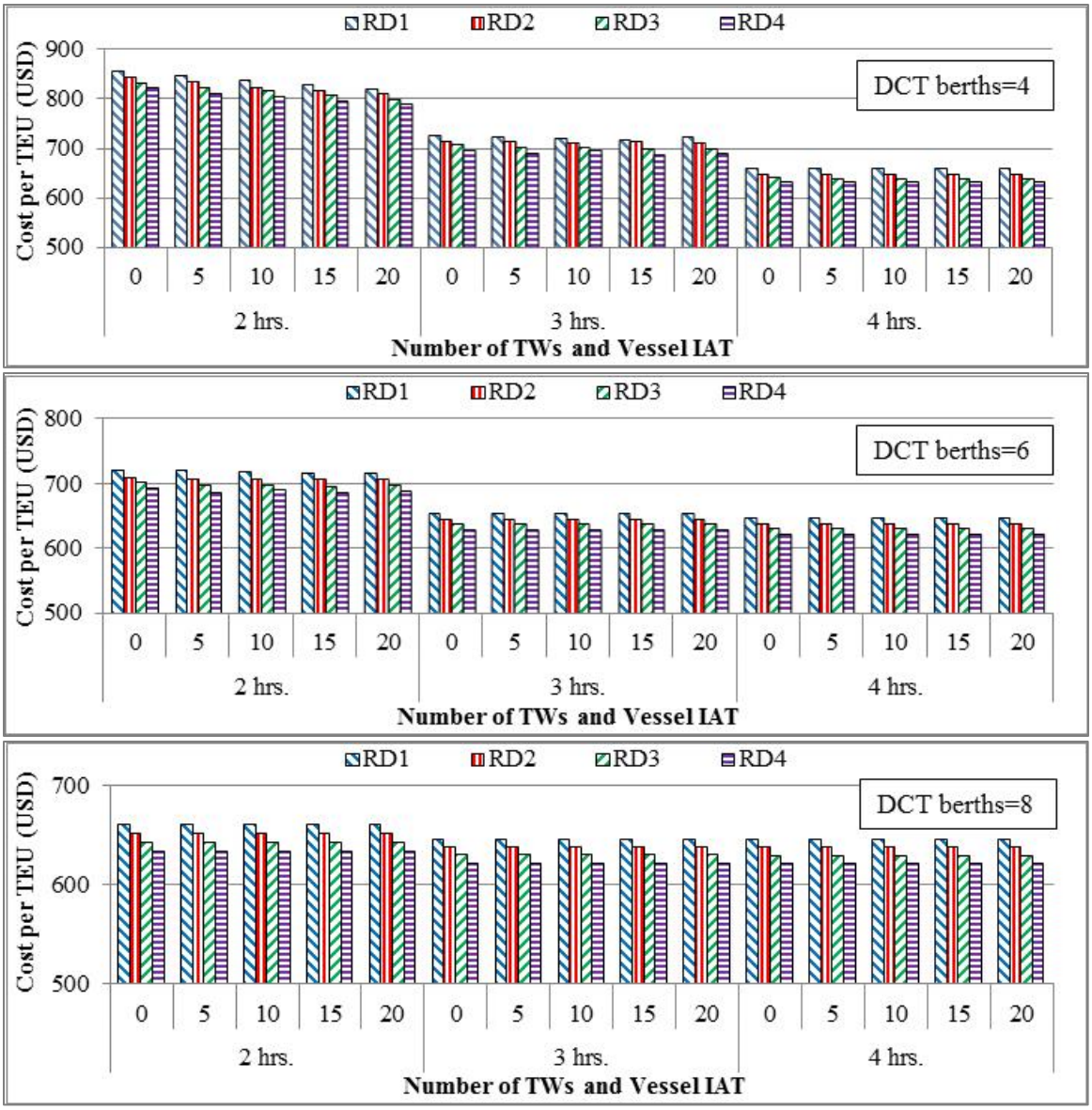


Figure 33. Cost per TEU by Number of TWs and IAT

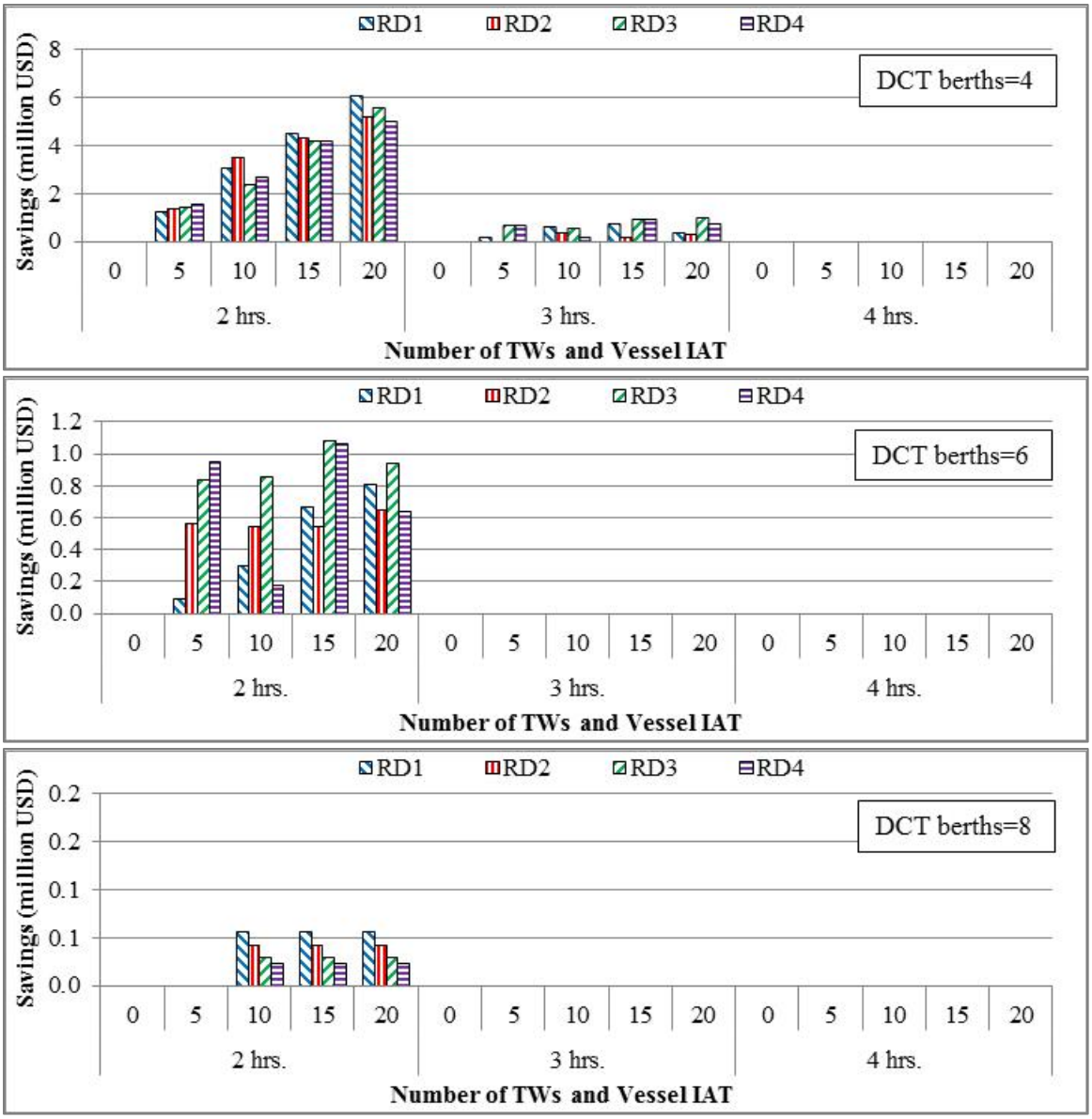


Figure 34. Total Savings by Number of TWs and IAT

TW utilization at MUT. Another important step during evaluation of the berthing policy was comparing the amount of diverted vessels to the number of available TWs. Results of this analysis are presented in Figure 35, where the x-axis of each graph has two components: a) the number of available TWs at MUT, and b) arrival pattern of vessels. The upper right corner of each chart denotes the number of available berths at DCT. For example, the second from the left group of bars at the top chart (see Figure 35) indicates that for the case of 5 TWs, high demand period (IAT = 2 hrs.), and 4 DCT berths, all TWs (TW utilization = 5) will be utilized by DCT vessels.

It can be noticed that TW utilization increases with more frequesnt vessel arrivals (i.e., high demand period) and lower DCT capacity (e.g., DCT configuration with 4 berths). The number of diverted vessels decreases (as expected) during low demand periods (e.g., IAT = 4 hrs.) and high DCT berth capacity (e.g., 8 berths). In this study TWs were relatively tight (with duration varying between 10 hrs. and 20 hrs. only), since MUT was assumed to have frequent arrivals of its vessels. From the study results it can be anticipated that the number of diverted vessels should increase with TW duration, as the number of candidates for service at MUT will increase, and the diverted vessels will be able to request lower handling rates and still complete service within the allocated TW. Negotiating TW duration is left for the future research.

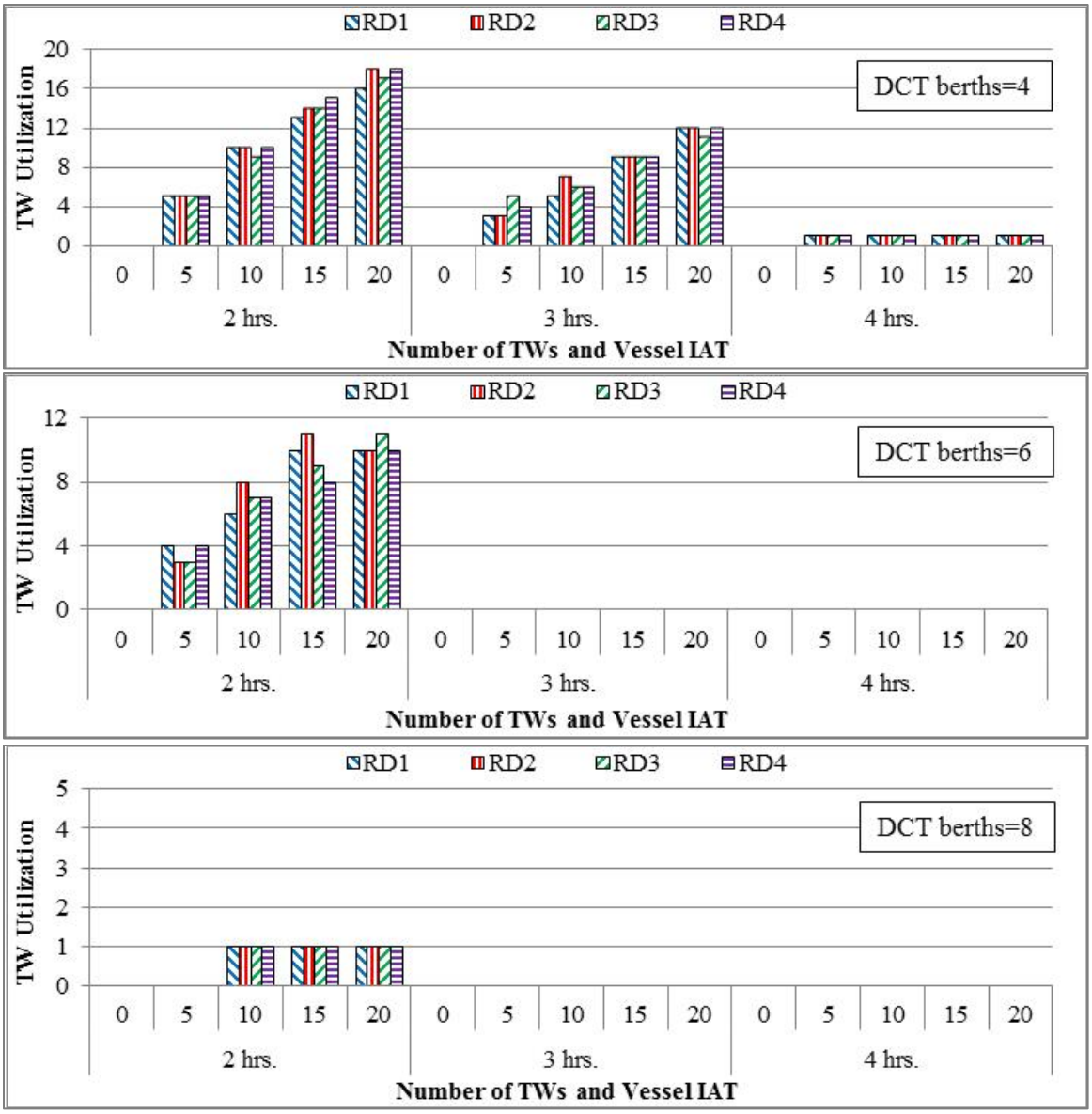


Figure 35. TW Utilization by Number of TWs and IAT

Conclusions and Future Research Avenues

In this paper a berth scheduling policy for marine container terminals with excessive demand was proposed, where vessels can be diverted for service to another terminal. A Memetic Algorithm that utilized two groups of local search heuristics was developed to solve the mathematical formulation, suggested to model the berthing policy.

The proposed policy showed greater savings for scenarios with higher demand and lower capacity at DCT. Savings of the DCT operator increased with the number of available TWs at MUT, while no substantial savings were observed for low demand periods and high capacity at DCT. The developed model can also be used as a tool to assist terminal operators in price setting/negotiating of container handling rates during high/medium demand periods. Future research could focus on: a) cost functions for penalties/premiums based on vessel size and load; b) vessel priorities; c) multiple vessel service per time window, d) adaptive mutation operators to improve solution quality and convergence rates; and e) vessel assignment heuristics during mutation.

5. FLEET DEPLOYMENT PROBLEM WITH VARIABLE SAILING SPEEDS AND PORT HANDLING TIMES

Introduction

Along with MCT operators liner shipping companies also aim to enhance efficiency of their operations. Many of liner shipping companies are slowing down their vessels. Such strategy leads to significant bunker consumption cost savings, which may comprise up to 75% of the total vessel operational costs (Ronen, 2011). Psaraftis and Kontovas (2013) outline two major alternatives of decreasing vessel sailing speed: a) building vessels with reduced horsepower engines (i.e., reduce the maximum possible vessel sailing speed), and b) slow steaming (i.e., a vessel sails at lower than the designed speed). The latter alternative is used more often in practice by liner shipping companies. "COSCO's container arm decreased fuel spending by 18 percent in the first half of the year (2014) through slow sailing, according to the company's first-half earnings statement" (Cargo Business, 2014). Maersk, the largest liner shipping company in the world, was even able to reduce their freight rates due to additional cost savings, achieved by slow steaming (Cargo Business, 2014). However, "off-schedule ships, particularly the mega-ships that are slow sailing to save costs, are also a factor…causing port congestion" (Cargo Business, 2014). Drewry Maritime Research indicated that "Asia-Europe trade was the least reliable during August-October (2014) with only 58 percent of ships arriving on-time", which is considered as unacceptable for many shippers (Cargo Business, 2014).

This chapter proposes a new collaborative agreement between a liner shipping company and marine container terminal operators, which can improve operations of both

players. According to this agreement, a liner shipping company negotiates handling rates with each terminal operator. Port handling charges increase, if faster service is requested. The fleet deployment problem studied herein was formulated as a mixed integer non-linear programming model. The original formulation was linearized and solved efficiently using CPLEX.

Overview of the Relevant Literature

The problem of vessel routing and scheduling in liner shipping received a lot of attention from researchers and practitioners, especially during the last ten years. In general, decisions that have to be made by a liner shipping company can be divided in three levels (Meng, Wang, Andersson, & Thun, 2014): a) strategic, b) tactical, and c) operational. At the strategic level, a liner shipping company should make long-term decisions (e.g., fleet size and mix, alliance strategy, network design). As for the tactical level, a liner shipping company makes medium-term decisions (e.g., frequency determination, fleet deployment, speed optimization, schedule construction). At the operational level, a liner shipping company makes short-term decisions (e.g., cargo booking, cargo routing, vessel rescheduling, potential reject of cargo). In this dissertation the literature review is mostly focused on studies, considering tactical level problems with emphasis on variability/uncertainty of vessel sailing speeds and/or port times.

Fagerholt (2001) formulated a vessel scheduling problem as a multi-ship pick-up and delivery problem with soft TWs (m-PDPSTW), when TW violations were allowed and could be controlled. The objective minimized the total transportation and inconvenience costs. A set partitioning based algorithm was proposed to solve the problem. Numerical experiments indicated that the suggested algorithm was substantially

affected with increasing problem size. Chuang, Lin, Kung, and Lin (2010) developed a fuzzy Evolutionary Algorithm (EA) to solve the containership routing problem, taking into account uncertainty in sailing and port times. The objective aimed to maximize the total profit, estimated as difference between the total revenue and the total route expenses. Fuzzy logic was applied for modeling uncertainty in sailing and port times. Numerical experiments demonstrated efficiency of the proposed methodology and the solution approach. Fagerholt, Laporte, and Norstad (2010) studied the sailing speed optimization problem, aiming to minimize the total fuel consumption. Possible vessel arrival times were discretized, and then a directed acyclic graph was constructed. The resulting problem was solved as the shortest path problem. Computational experiments demonstrated that the suggested methodology provided substantial fuel consumption savings.

Golias et al. (2010a) presented a new discrete dynamic berth scheduling problem (DDBSP), taking into account estimated arrival time to the next port of call for each vessel. The objective of the model minimized the total vessel service time, delayed departures, fuel consumption, and vessel emissions. The authors applied an EA to solve the problem. Gelareh and Meng (2010) developed a mixed integer non-linear programming model for a short-term fleet deployment problem of liner shipping operations. The objective of the program aimed to minimize the total transportation costs, taking into account TW constraints. The original problem was reformulated as a linear program and then solved using CPLEX. Numerical experiments were performed for transpacific, transatlantic, and Asia-Europe liner shipping routes. It was mentioned that CPLEX was not able to provide a solution for large size instances. Du et al. (2011)

presented a bi-objective model for a continuous DBSP (CDBSP), where the first objective minimized the total vessel fuel consumption, while the second one minimized the total vessel late departures. A second order cone programming (SOCP) technique was applied to the objective, minimizing the total vessel fuel consumption. A heuristic was developed to solve the problem. Computational examples indicated that the strategy of introducing variable vessel arrivals led to lower emissions, comparing to the constant vessel arrival case.

Norstad et al. (2011) suggested a mixed integer non-linear formulation for the tramp vessel routing and scheduling problem with speed optimization. The objective of the model aimed to maximize the total profit from operating the vessel fleet. A set of heuristics were developed to solve the problem. Computational examples indicated that higher discretization level could improve the objective function values, but affected the computational time. Meng and Wang (2011) developed a model to determine service frequency, fleet deployment plan, and sailing speed for a long-haul liner service route. The objective of a non-linear mixed-integer program minimized the total daily operating costs. A linearized problem was solved using Branch-and-Bound (B&B) algorithm. Numerical experiments were conducted for SCX liner service route.

Qi and Song (2012) considered the problem of the optimal vessel schedule design in the liner shipping route, taking into account the impact of port time uncertainty. The objective aimed to minimize the total expected fuel consumption and penalties due to vessel delays. Simulation-based stochastic approximation methods were employed to solve the problem. The port time was assumed to follow the uniform distribution. Six scenarios with different levels of port time uncertainty (ranging from U[0;0] to U[0;20]

hrs.) were considered. Computational examples indicated that increasing uncertainty in port times caused greater fuel consumption for a given route. Wang and Meng (2012a) presented a liner shipping route schedule model, capturing uncertainty in sailing and port times. The objective of an integer non-linear program minimized the total transportation cost, including weekly vessel operating cost and bunker cost. The port time uncertainty was modeled using predetermined probability distribution (uniform), while the sailing time contingency was estimated based on realization of a port time and an additional parameter, denoting hedge against contingency (proportional to the length of a voyage leg). The original program was reformulated as a linear problem and solved using CPLEX. A computational example was provided for Asia-Europe-Oceania shipping network. It was found that sailing and port time contingency could result in deployment of more vessels on a given route. Lower speeds were suggested for scenarios with high unit bunker costs.

Wang and Meng (2012b) formulated the vessel sailing speed optimization problem, aiming to minimize the total transportation cost. The original problem was linearized using an outer-approximation method and solved using CPLEX. Numerical experiments, conducted for Asia-Europe-Oceania network, indicated efficiency of the proposed methodology and the solution algorithm. Wang and Meng (2012c) studied a liner shipping route scheduling problem, taking into account possible uncertainties in port waiting time (due to congestion) and container handling time. The objective of a mixed integer non-linear program minimized the total transportation cost, including three components: 1) weekly vessel operating cost, 2) bunker cost, and 3) late handling cost. Uncertainties in port waiting and handling times were modeled using the truncated

normal distributions. The original problem was linearized and solved using CPLEX. Sample average approximation (SAA) was used to address stochastic port waiting and service times. Numerical experiments were conducted for Asia-America-Europe liner shipping route. It was found that a liner shipping company could improve robustness of its schedule by adding more vessels. Potential errors, caused by the linear approximation were discussed as well.

Yao, Ng, and Lee (2012) developed a bunker fuel management strategy for liner shipping companies, aiming to minimize the total bunker fuel costs and the revenue loss due to weight of the bunker fuel. Fuel prices and discounts varied from port to port. The original model was linearized using a piecewise approximation method and solved using CPLEX. Numerical experiments were provided for Asia-Europe-Express service and Atlantic-Pacific-Express service. Brouer, Dirksen, Pisinger, Plum, and Vaaben (2013) studied a Vessel Schedule Recovery Problem (VSRP), taking into account disruptions that might occur in liner shipping due to inclement weather conditions, port closures, and other contingencies. The problem was formulated as a mixed integer linear program. The following disruptive scenarios were modeled: a) vessel delays due to weather conditions, b) a port closure, c) a berth prioritization, when two vessels arrive simultaneously to the port and are scheduled at the same berth, and d) an expected port congestion. The following countermeasures were suggested to mitigate effects of the uncertainty: a) port omitting, b) increasing vessel speed, c) swap ports of call, and d) accept vessel delays. Generated problem instances were solved using CPLEX. It was found that the suggested methodology could yield up to 58% if the total cost savings.

Wang, Meng, and Liu (2013a) formulated the model for containership scheduling with a transit-time-sensitive demand, maximizing the total profit from the given vessel route. The problem was solved using conic quadratic programming and B&B. Computational examples demonstrated that the elastic demand affected the number of deployed vessels, sailing speed, and computational efficiency. Wang, Alharbi, and Davy (2014) presented a mixed integer non-linear optimization model for the liner shipping route schedule, taking into account that each port had a set of TWs. The objective minimized the total transportation costs. The original problem was linearized and solved using CPLEX. Numerical experiments indicated that increasing duration of port TWs decreased the total cost, while increasing value of goods required higher vessel sailing speed.

Problem Description

Liner shipping route. In this study a liner shipping route with $I = \{1, \dots, n\}$ ports of call was considered (see Figure 36). Each port is assumed to be visited once[11] and the sequence of visited ports (i.e., port rotation) is already known. The latter decision is made by a liner shipping company at the strategic level (Meng et al., 2014). A vessel sails between two subsequent ports i and $i + 1$ along leg i. The liner shipping company provides a weekly service at each port of call. The terminal operator at each port sets a specific arrival TW [tw_i^e – the earliest start at port i, tw_i^l– the latest start at port i], during which a vessel should arrive at the port (can be up to 1-3 days depending on the port).

[11] This assumption does not limit generality of the suggested methodology and can be relaxed as needed, i.e., some ports can be visited more than once

Weekly demand (TEUs) at each port is known while the quantity of containers transported by alliance partners is excluded from the total weekly demand, as this decision is usually made by the liner shipping company at the strategic level (Meng et al., 2014).

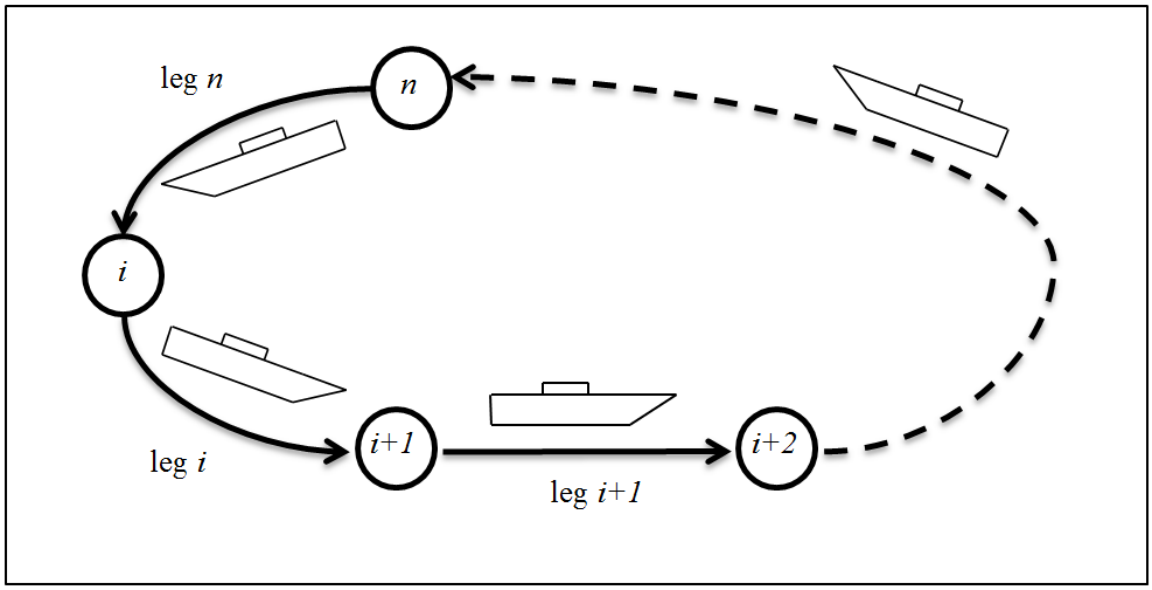


Figure 36. Illustration of a Shipping Route

Service policy agreement description. Terminal operators have various contractual agreements with the liner shipping company, according to which each terminal operator offers a set of handling rates $S_i = \{1, \dots, s_i\}\ \forall i \in I$ to the liner shipping company. If faster service is requested, the port handling time for a given vessel decreases, but port handling charges, imposed to the liner shipping company, increase. Note that reduced handling time at a port may result in bunker consumption cost savings, since a vessel can sail at a lower speed to the next port of call.

Vessel arrivals. The following scenarios of vessel arrivals will be modeled in this study:

a. If a vessel arrives within a set arrival TW, no penalties will be imposed to the liner shipping company (see Figure 37A).

b. In certain cases a vessel, departing from port i, may not be able to arrive at the next port $i+1$ before the earliest start tw_{i+1}^{e}, even when sailing at the lowest possible speed v^{min} (see Figure 37B). In such cases we assume that the vessel will wait at a dedicated area at port i to ensure arrival within the allocated TW at port $i+1$[12]. The port waiting time wt_i can be estimated as $wt_i = tw_{i+1}^{e} - \frac{l_i}{v_i} - t_i^d$ (Figure 37C)[13], where v_i is the sailing speed on leg i, l_i is length of leg i, t_i^d is departure time from port i. It is assumed that additional costs are incurred, when a vessel waits at the given port.

c. If a vessel arrives after the end of the latest start tw_{i+1}^{l} (see Figure 37D), monetary penalties are imposed to the liner shipping company (in USD/hr.), but the service of vessel will still start upon its arrival[14]. The penalty value is assumed to linearly increase with late arrival hours lt_i.

[12] Technically the vessel can also wait at port $i+1$, or split waiting times between ports i and $i+1$. Future research may focus on evaluation of different decisions regarding the port waiting time

[13] In section 5.4 we prove that v_i is equal to v^{min}

[14] It is assumed that the liner shipping company under consideration can negotiate such an agreement

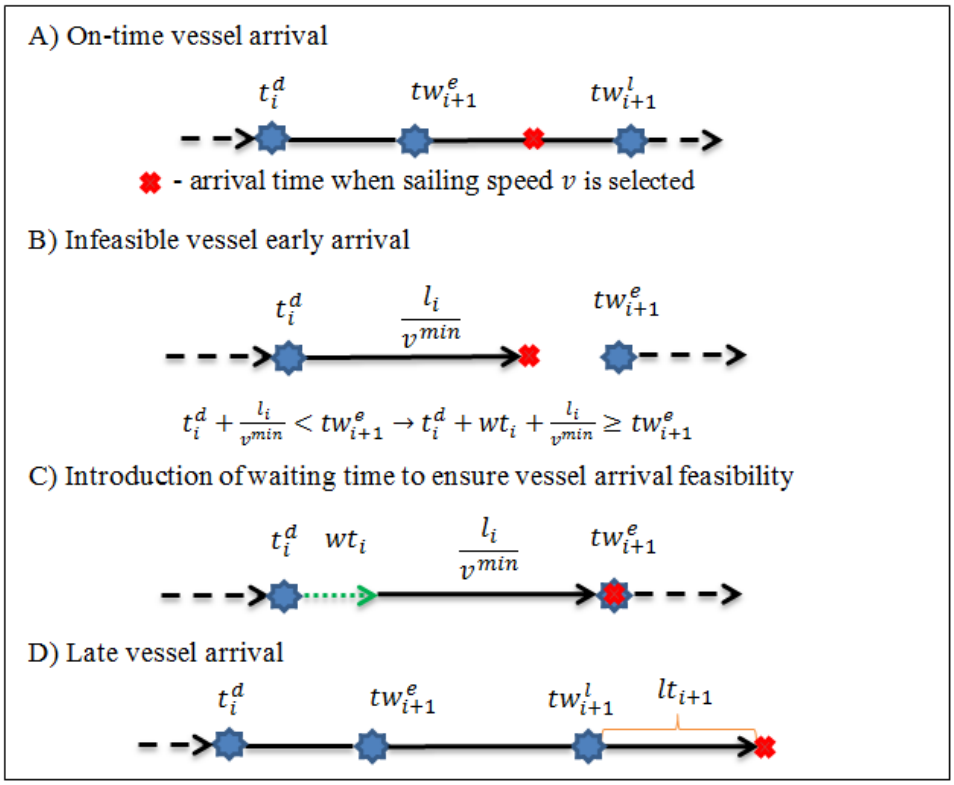


Figure 37. Vessel Arrival Cases

Bunker consumption. It is assumed that a vessel fleet for a given route is homogenous, which is a common practice, as revealed in the literature (Wang & Meng, 2012a-c; Wang et al., 2013a; Wang et al., 2014), and the relationship between the bunker consumption and the vessel speed is as follows:

$$q(\overline{v}) = q^*(v^*) \times \left(\frac{\overline{v}}{v^*}\right)^{\alpha} = \gamma \times (\overline{v})^{\alpha} \tag{28}$$

where:

$q(\overline{v})$ – daily bunker consumption (tons of fuel/day);

$\overline{v}$ – average daily sailing speed (knots);

$q^*(v^*)$ – daily bunker consumption when sailing at the designed speed (tons of fuel/day);

v^* – design sailing speed (knots);

α, γ – coefficients calibrated from the historical data;

Generally, additional regression analysis should be conducted to determine the values of α and γ for each vessel in the fleet (Du et al., 2011; Wang & Meng, 2012b; Yao et al., 2012, etc.). Due to lack of data, the most common values from the literature (Psaraftis & Kontovas, 2013; Wang & Meng, 2012b) are adopted in this study (i.e., $a = 3$ and $\gamma = 0.012$). Once the liner shipping company decides on a sailing speed between consecutive ports, it is assumed to remain constant. Factors affecting the vessel speed during voyage (e.g., weather conditions, wind speed, height of waves, etc.) are not considered. The fuel consumption by auxiliary engines was included in the weekly vessel operating cost.

Note that bunker consumption per nautical mile $f(v_i)$ at leg i can be estimated as follows:

$$f(v_i) = q(v_i) \times \left(\frac{t_i}{24}\right) \times \frac{1}{l_i} = \gamma \times (v_i)^a \times \frac{l_i}{24 \times v_i} \times \frac{1}{l_i} = \frac{\gamma \times (v_i)^{a-1}}{24} \ \forall i \in I \tag{29}$$

where:

t_i – sailing time between ports i and $i + 1$ (hrs.)

Decisions. The problem, considered in this study, can be classified as a tactical level problem and will be referred to as the fleet deployment problem FDP. In this problem the liner shipping company determines the following:

1) Number of vessels assigned at the given route in order to provide weekly service at each port (decision on fleet size and mix is assumed to be made at the strategic level, Meng et al., 2014)

2) Handling time (or handling rates) at each port, taking into account TW constraints and increasing charges for faster service at each port

3) Port waiting time to ensure feasibility of arrival at the next port of call

4) Sailing speed between consecutive ports, taking into account TW constraints at each port and associated bunker consumption costs

5) Vessel late arrival fees.

A liner shipping company sets a maximum quantity of vessels that can be deployed at any given route ($q \leq q^{max}$) and sets limits on lower and upper vessel sailing speed ($v^{min} \leq v_i \leq v^{max}\ \forall i \in I$). The minimum sailing speed v^{min} is selected to reduce wear of the vessel's engine (Wang et al., 2013b), while the maximum sailing speed v^{max} is defined by the capacity of the vessel's engine (Psaraftis & Kontovas, 2013). Note that all decisions are interrelated. Selecting lower sailing speed reduces the bunker consumption, but may require deployment of more vessels at the given route to ensure that weekly service is met, which increases the total weekly operating cost (e.g., crew costs, maintenance, repairs, insurance, etc.). Various port handling rates further allow the liner shipping company to weigh different options between sailing and port handling times (e.g., faster handling rate reduces the service time at a given port, which may allow sailing at a lower speed to the next port of call). On the other hand higher handling rates may not always be favorable as they may lead to the vessel waiting, once service is completed (see vessel arrival case b in "Vessel arrivals" section).

Mathematical Formulation

This section presents a mixed integer non-liner mathematical model for the fleet deployment problem with variable vessel sailing speeds and port handling times.

Nomenclature

Sets

$I = \{1, \dots, n\}$	set of ports to be visited
$S_i = \{1, \dots, s_i\}$	set of available handling rates[15] at port $i \in I$

Decision variables

$v_i \ \forall i \in I$	vessel sailing speed at leg i, connecting ports (i) and $(i+1)$
$x_{is} \ \forall i \in I, s \in S_i$	=1 if handling rate s is selected at port i (=0 otherwise)

Auxiliary variables

q	number of vessels deployed at the given route
$t_i^a \ \forall i \in I$	arrival time at port i (hrs.)
$t_i^d \ \forall i \in I$	departure time from port i (hrs.)
$wt_i \ \forall i \in I$	hours of waiting time of a vessel at port i
$t_i \ \forall i \in I$	vessel sailing time at leg i, connecting ports (i) and $(i+1)$
$f(v_i) \ \forall i \in I$	bunker consumption at leg i at sailing speed v_i (tons of fuel/nmi)
$lt_i \ \forall i \in I$	hours of vessel late arrival at port i

Parameters

β	unit bunker cost (USD/ton)
c^{OC}	vessel weekly operating cost (USD/week)
c^w	hourly port waiting cost (USD)
c^{lt}	hourly delayed arrival penalty (USD)
$l_i \ \forall i \in I$	length of leg i (nmi)
v^{min}	minimum vessel sailing speed (knots)
v^{max}	maximum vessel sailing speed (knots)
q^{max}	maximum number of deployed vessels
$p_{is} \ \forall i \in I, s \in S_i$	vessel handling time at port i under handling rate s (hrs.)
$tw_i^e \ \forall i \in I$	the earliest start at port i (hrs.)
$tw_i^l \ \forall i \in I$	the latest start at port i (hrs.)
$sc_{is} \ \forall i \in I, s \in S_i$	handling cost at port i under handling rate s (USD/hrs.)

The objective function (30) minimizes the total route service cost, which includes 5 components: 1) total vessel weekly operating cost, 2) total bunker consumption cost, 3) total port handling cost, 4) total port waiting cost, and 5) total late arrival penalty.

[15] Set of handling rates contains indexes of available handling rates (i.e., if a terminal operator at port i offers two handling rates 75 TEUs/hr. and 50 TEUs/hr., then $S_i = \{1,2\}$)

FDP: $min[c^{OC}q + \beta \sum_{i\in I} l_i f(v_i) + \sum_{i\in I}\sum_{s\in S_i} p_{is}x_{is}sc_{is} + \sum_{i\in I} c^{w}wt_i + \sum_{i\in I} c^{lt}lt_i]$ (30)

Subject to:

Constraints set (31) indicate that only one handling rate can be selected at each port of call.

$$\sum_{s\in S_i} x_{is} = 1 \; \forall i \in I \tag{31}$$

Constraints set (32) calculate a vessel sailing time between ports i and $i+1$.

$$t_i = \frac{l_i}{v_i} \; \forall i \in I \tag{32}$$

Constraints set (33) ensure that a vessel cannot arrive at port $i \in I$ before the agreed TW.

$$t_i^a \geq tw_i^e \; \forall i \in I \tag{33}$$

Constraints sets (34) and (35) compute waiting time at port $i \in I$, necessary to ensure feasibility of arriving to the next port of call.

$$t_i^a + \sum_{s\in S_i}(p_{is}\, x_{is}) + wt_i + t_i \geq tw_{i+1}^e \; \forall i < |I| \tag{34}$$

$$t_i^a + \sum_{s\in S_i}(p_{is}\, x_{is}) + wt_i + t_i - 168q \geq tw_1^e \; \forall i = |I| \tag{35}$$

Constraints set (36) calculate a vessel departure time from port $i \in I$.

$$t_i^d = t_i^a + \sum_{s\in S_i}(p_{is}\, x_{is}) + wt_i \; \forall i \in I \tag{36}$$

Constraints set (37) estimate hours of late arrival at port $i \in I$.

$$lt_i \geq t_i^a - tw_i^l \; \forall i \in I \tag{37}$$

Constraints sets (38) and (39) compute a vessel arrival at the next port of call $i \in I$.

$$t_{i+1}^a = t_i^d + t_i \; \forall i < |I| \tag{38}$$

$$t_1^a = t_i^d + t_i - 168q \ \forall i = |I| \tag{39}$$

Constraints set (40) ensure weekly service frequency (168 denotes the total number of hours in a week). The right-hand-side of an equality estimates the total turnaround time of a vessel at the given route (where the first component is the total sailing time, the second component is the total port handling time, and the third component is the total port waiting time).

$$168q \geq \sum_{i \in I} t_i + \sum_{i \in I} \sum_{s \in S_i} (p_{is} x_{is}) + \sum_{i \in I} wt_i \tag{40}$$

Constraints set (41) ensure that the number of vessels to be deployed at the given route should not exceed the number of available vessels.

$$q \leq q^{max} \tag{41}$$

Constraints set (42) show that a vessel sailing speed should be within specific limits.

$$v^{min} \leq v_i \leq v^{max} \ \forall i \in I \tag{42}$$

Constraints (16) – (18) define ranges of parameters and variables.

$$x_{is} \ \in \{0,1\} \ \forall i \in I, s \in S_i \tag{43}$$

$$q, q^{max} \in N \ \forall i \in I \tag{44}$$

$$v_i, t_i^a, t_i^d, wt_i, t_i, f(v_i), lt_i, \beta, c^{OC}, c^w, c^{lt}, l_i, v^{min}, v^{max}, p_{is}, tw_i^e, tw_i^l, sc_{is} \in R^+ \ \forall i \in I, s \in S_i \tag{45}$$

Solution Approach

Bunker consumption linear approximation. The non-linear bunker consumption function can be approximated using piecewise linear functions with various number of segments.

Note that different number of segments will result in different linear approximations with accuracy of the approximation (and computational time) increasing with the number of segments. In this study **FDP** is linearized following a similar methodology to Wang and Meng (2012b-c), and Wang et al. (2013a-b, 2014). In addition to the non-linear objective function, nonlinearities of **FDP** also stem from constraints set (32). To address the latter nonlinearity, the vessel sailing speed $v_i \; \forall i \in I$ is replaced by its reciprocal $y_i = 1/v_i \; \forall i \in I$. Once the sailing speed has been replaced by its reciprocal, let $G(y)$ be the bunker consumption function.

Examples of different linear approximation functions ($\overline{G_m}(y)$), each with a different number of m segments, are presented in Figure 38 and Table 9 for the bunker function: $G(y) = \frac{0.012 \times (y)^{-2}}{24}$. In this example vessel sailing speed v_i was assumed to range between $v^{min} = 10$ knots and $v^{max} = 25$ knots ($0.04 \leq y_i \leq 0.10$). The linear segments of each piecewise function $\overline{G_m}(y)$ are denoted by solid lines in Figure 38. Approximation results are presented in Table 9, where column 1 shows sailing speed; column 2 presents sailing speed reciprocal; column 3 shows the actual bunker consumption (provided by the non-linear bunker consumption function); columns 4 through 7 present bunker consumption values, estimated using piecewise approximating functions with different number of segments m; columns 8 through 11 show approximation errors for each piecewise function.

From the results in Table 9 we observe that accuracy increases with the number of segments, while the error, as speed changes, does not follow any pattern (e.g., smaller errors for lower speeds). Note that for $m = 10$ the error is very close to zero. However, increasing m may negatively affect the computational time. A trade-off between the

bunker consumption approximating function accuracy (and in turn the accuracy of the optimal solution) and the computational time will be analyzed in the numerical experiments section.

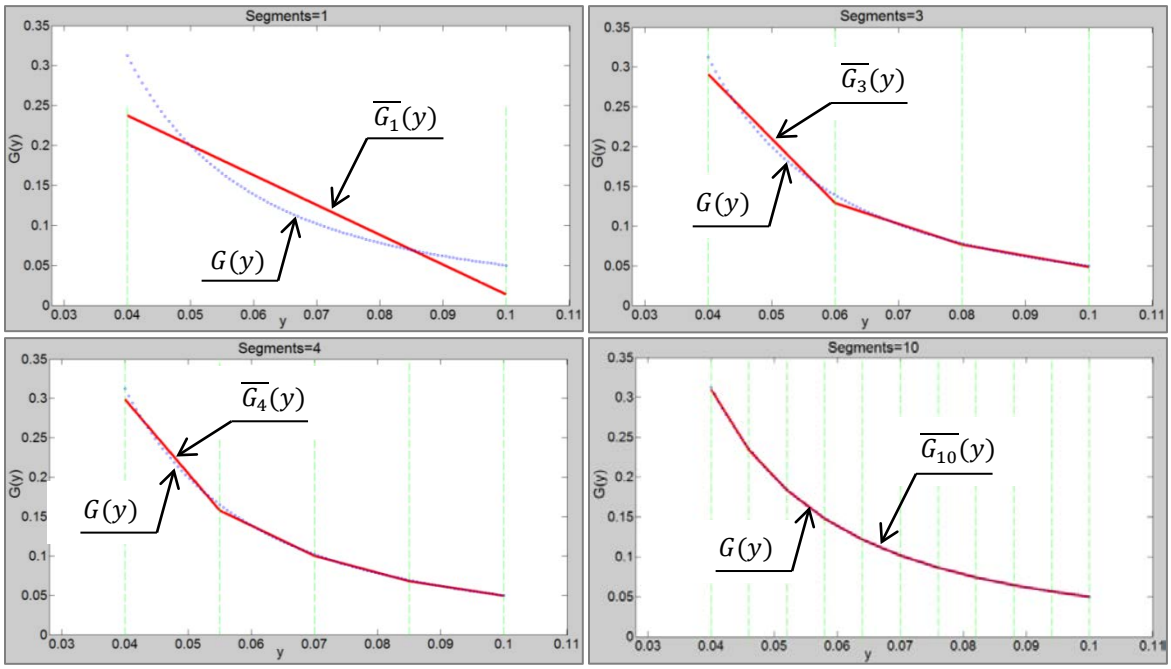


Figure 38. Bunker Consumption Approximating Function Examples

Table 9

Bunker Consumption Approximating Function Examples

		Bunker Consumption (tons of fuel/nmi)					% of error: $\{G(y) - \overline{G_m}(y)\}/\, G(y)$			
v	$y = 1/v$	$G(y)$	$\overline{G_1}(y)$	$\overline{G_3}(y)$	$\overline{G_4}(y)$	$\overline{G_{10}}(y)$	m=1	m=3	m=4	m=10
25	0.040	0.3125	0.2376	0.2911	0.2989	0.3100	24%	7%	4%	1%
24	0.042	0.2880	0.2301	0.2748	0.2801	0.2847	20%	5%	3%	1%
22	0.045	0.2420	0.2189	0.2505	0.2519	0.2467	10%	-4%	-4%	-2%
20	0.050	0.2000	0.2002	0.2100	0.2049	0.2005	0%	-5%	-2%	0%
18	0.056	0.1620	0.1778	0.1613	0.1540	0.1598	-10%	0%	5%	1%
16	0.063	0.1280	0.1517	0.1211	0.1271	0.1259	-19%	5%	1%	2%
14	0.071	0.0980	0.1218	0.1002	0.0981	0.0991	-24%	-2%	0%	-1%
12	0.083	0.0720	0.0770	0.0724	0.0723	0.0725	-7%	-1%	0%	-1%
10	0.100	0.0500	0.0135	0.0485	0.0495	0.0499	73%	3%	1%	0%

Next the linearized formulation of **FDP** is presented, where vessels sailing speed v_i is replaced by its reciprocal y_i, and the non-linear bunker consumption function $G(y)$ is replaced by its approximation $\overline{G_m}(y)$.

Linearized mixed integer formulation. Let $\boldsymbol{K} = \{1,2, \dots . m\}$ be the set of linear segments of the piecewise function $\overline{G_m}(y)$. Denote as $st_k, ed_k, k \in K$ the speed reciprocal values at the start and end (respectively) of linear segment k; $SL_k, IN_k,\ k \in K$ the slope and an intercept of linear segment k (obtained from a piecewise linear regression analysis); and M_1, M_2 as sufficiently large positive numbers. Then FDP can be reformulated as a linear problem as follows (equations 19 through 25):

FDPL: $Z = min[c^{OC}q + \beta \sum_{i\in I}\left(l_i \sum_{k\in K} \overline{G_k}(y_i)\right) + \sum_{i\in I}\sum_{s\in S_i} p_{is}x_{is}sc_{is} + \sum_{i\in I} c^w wt_i + \sum_{i\in I} c^{lt} lt_i]$ (46)

Subject to:

Constraints sets (31), (33)-(41), (43)-(45)

$$\sum_{k\in K} b_{ik} = 1\ \forall i \in I \tag{47}$$

$$st_k b_{ik} \leq y_i\ \forall i \in I, k \in K \tag{48}$$

$$ed_k + M_1(1 - b_{ik}) \geq y_i\ \forall i \in I, k \in K \tag{49}$$

$$\overline{G_k}(y_i)\ \geq SL_k y_i +\ IN_k - M_2(1 - b_{ik})\ \forall i \in I, k \in K \tag{50}$$

$$t_i = l_i y_i\ \forall i \in I \tag{51}$$

$$1/v^{max} \leq y_i \leq 1/v^{min}\ \forall i \in I \tag{52}$$

In **FDPL** constraints set (47) ensure that only one segment k will be selected for approximation of the bunker consumption function at leg i. Constraints sets (48) and (49) define range of vessel sailing speed reciprocal values, when segment k is selected

for approximation of the bunker consumption function at leg i. Constraints set (50) estimate the approximated bunker consumption at leg i. Constraints set (51) calculate a vessel sailing time between ports i and $i+1$. Constraints set (52) show that a reciprocal of vessel sailing speed should be within specific limits. Positive number M_1 was introduced to ensure that each segment $k \in K$ of $\overline{G_k}(y)$ function approximates a non-linear function $G(y)$ only for a specific range of y. Positive number M_2 was introduced to estimate the approximated bunker consumption value $\overline{G_k}(y)$ for a given y. Strict lower bounds for M_1 and M_2 can be defined as follows: $M_1 = \frac{1}{v^{min}}$, $M_2 = SL_1 \times \frac{1}{v^{max}} + IN_1$. Note that M_1 and M_2 can be replaced in constraints sets (22) and (23) by $M = max\{\frac{1}{v^{min}}; SL_1 \times \frac{1}{v^{max}} + IN_1\}$. **FDPL** can be solved efficiently using CPLEX even for large size instances (as discussed in detail in the numerical experiments section).

Note on bunker consumption estimation method. In the available relevant literature (Wang & Meng 2012b-c; Wang et al., 2013b, 2014) researchers have used a similar method to linearize bunker consumption, but a different method to calculate the bunker consumption function value. In the remainder of the manuscript we will refer to the already published method as AP-1 and to the one proposed herein as AP-2. Under AP-2 bunker consumption is calculated via constraints set (50), while under AP-1 using the following equation:

$$\overline{G_k}(y_i) \geq SL_k y_i + IN_k \; \forall i \in I, k \in K \tag{53}$$

The main difference in the two equations is the component $-M_2 \times (1 - b_{ik})$ in equation (50) that employs an additional decision variable (b_{ik}), which will increase the computational time, but as shown in this section improves accuracy in certain cases. The

extent of the computational time increase will be discussed in the numerical experiments section. AP-1 and AP-2 were compared in terms of their accuracy in estimating bunker consumption using various piecewise linear functions. Findings indicate that AP-1 is accurate if and only if segment slopes are monotonically increasing and does not guarantee that the correct segment will be selected. On the other hand AP-2 accuracy is not affected by the geometry of the piecewise linear function and always selects the correct segment to calculate the approximated vessel speed. Next we provide a numerical example to demonstrate the accuracy improvement of AP-2 as compared to AP-1.

Consider the bunker consumption function: $G(y) = \frac{0.012 \times (y)^{-2}}{24}$, and two different piecewise linear approximations $\overline{G_5^1}(y)$ and $\overline{G_5^2}(y)$, as shown in Figure 39. Both $\overline{G_5^1}(y)$ and $\overline{G_5^2}(y)$ have 5 segments ($m = 5$), but different shapes. Assume that at a given leg i a vessel sailing speed reciprocal of $y_i = 0.07$ is chosen by the optimization model. For approximation $\overline{G_5^1}(y)$ both AP-1 and AP-2 will select the same segment ($k = 3$) and return the same bunker consumption value of: $\overline{G_5^1}(y) = 0.1028$. However, for approximation $\overline{G_5^2}(y)$ AP-1 selects segment 2 instead of 3, and returns a higher bunker consumption value (0.1227 when $k = 2$ vs. 0.1097 when $k = 3$). AP-2 selects segment 3, since $st_3 < y_i < ed_3$ (i.e., $0.064 < 0.07 < 0.076$), and reduces the approximation error (see Figure 4, where the circle, representing the bunker consumption obtained by AP-2, is closer to $G(y)$ as compared to the triangle, representing the bunker consumption obtained by AP-1).

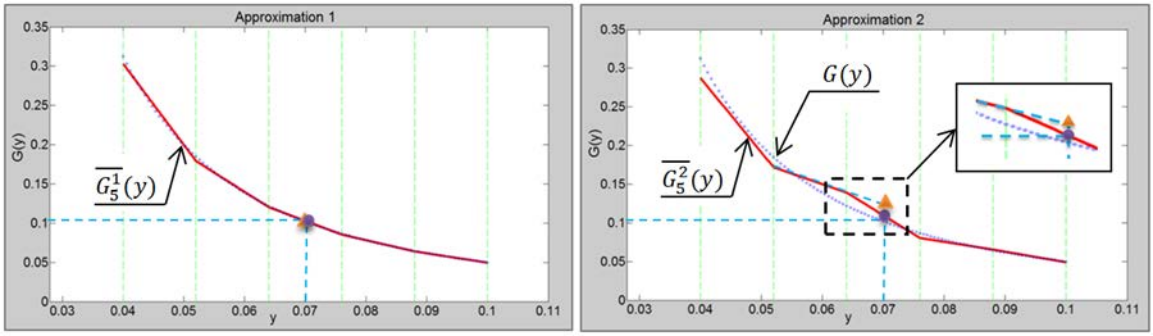


Figure 39. Examples of Different Piecewise Linear Functions

Note: ▲ - bunker consumption using AP-1; ● - bunker consumption using AP-2; actual bunker consumption lies on the dotted $G(y)$ function

Bunker consumption values were estimated using $\overline{G_5^2}(y)$ for different values of sailing speed reciprocal y, varying from 0.05 to 0.08 with an increment of 0.005, and results are presented in Table 10. The second and third column show the segment selected by each method; columns 4 through 6 show the bunker consumption from AP-1, AP-2 and the non-linear bunker consumption function; while the last two columns show the percentage difference between the actual bunker consumption and that estimated by AP-1 and AP-2 respectively. We observe that AP-1 constantly overestimates bunker consumption and returns larger approximation errors as compared to AP-2. The latter can be explained by the fact that AP-1 always choses the greatest bunker consumption values without considering the segment of the piecewise linear approximation used. In the cases where both methods overestimate bunker consumption, AP-2 error is smaller.

Table 10
Comparison of AP-1 and AP-2

	y	Segment selected		Bunker Consumption (tons of fuel/nmi)			% of error: $\{G(y) - \overline{G_m}(y)\}/\, G(y)$	
		AP-1	AP-2	AP-1	AP-2	Actual $G(y)$	AP-1	AP-2
$\overline{G_5^2}(y)$	0.050	3	1	0.2075	0.1911	0.2000	-4%	4%
	0.055	3	2	0.1831	0.1637	0.1653	-11%	1%
	0.060	3	2	0.1586	0.1500	0.1389	-14%	-8%
	0.065	2	3	0.1364	0.1342	0.1183	-15%	-13%
	0.070	2	3	0.1227	0.1097	0.1020	-20%	-8%
	0.075	2	3	0.1090	0.0853	0.0889	-23%	4%
	0.080	2	4	0.0954	0.0754	0.0781	-22%	3%

Sailing speed selection when waiting at the port. As discussed previously, under case b a vessel departing from port i immediately after completion of handling operations will arrive at the next port of call $i+1$ before the earliest start tw_{i+1}^{e}, even when sailing at the lowest possible speed v^{min} (see Figure 37B). In such cases we assume that the vessel will wait at a dedicated area at port i to ensure arrival within the allocated TW at port $i+1$. The port waiting time wt_i can be computed as $wt_i = tw_{i+1}^{e} - \frac{l_i}{v_i} - t_i^d$. Next the study elaborates more on selecting vessel sailing speed v_i.

Proposition 1: *If $S^* = (v_i^*, x_{is}^*)$ is an optimal solution to **FDPL**, where a vessel has to wait at port i after completion of service, then $v_i^* = v^{min}$.*

Proof:

Let $Z(S)$ be the objective function value of a solution S to the problem. Assume that solution $S^* = (v_i^*, x_{is}^*)$ with $v_i^* = v^{min}$ is not optimal. Hence, there exist another solution $\acute{S} = (\acute{v}_\iota, x_{is}^*)$ with $\acute{v}_\iota \geq v^{min}$, such that $Z(\acute{S}) \leq Z(S^*)$. However, $\acute{v}_\iota \geq v^{min}$ => $\acute{wt}_\iota \geq wt_i^*$ => $Z(S^*) \geq Z(\acute{S})$. Thus, at the optimal solution of **FDPL**, where a vessel has to wait at port *i* after completion of service: $v_i^* = v^{min}$. □

Numerical Experiments

This section presents a number of numerical experiments to evaluate the proposed bunker consumption function estimation method and the efficiency of the proposed service policy agreement.

Input data description. French Asia Line 1 route (as shown in Figure 40), served by CMA CGM liner shipping company, was used as input data for this study. This route connects North Europe, North Africa, Malta, Middle East Gulf, and Asia. The port rotation for French Asia Line 1 route includes 18 ports of call (distance to the next port of call in nautical miles is presented in parenthesis, estimated using world seaports catalogue[16]), where the Port of Kelang (Malaysia) is visited twice:

1. Southampton, GB (571) → 2. Hamburg, DE (36) → 3. Bremerhaven, DE (309) → 4. Rotterdam, NL (364) → 5. Zeebrugge, BE (302) → 6. Le Havre, FR (2538) → 7. Malta, MT (4089) → 8. Khor al Fakkan, AE (199) → 9. Jebel Ali, AE (3741) → 10. Port Kelang, MY (2835) → 11. Ningbo, CN (87) → 12. Shanghai, CN (606) → 13. Xiamen, CN (955) → 14. Hong Kong, HK (375) → 15. Chiwan, CN (395) → 16. Yantian, CN (2045) → 17. Port Kelang, MY (7490) → 18. Tanger Med, MA (1367) → 1. Southampton, GB

[16] http://ports.com/sea-route

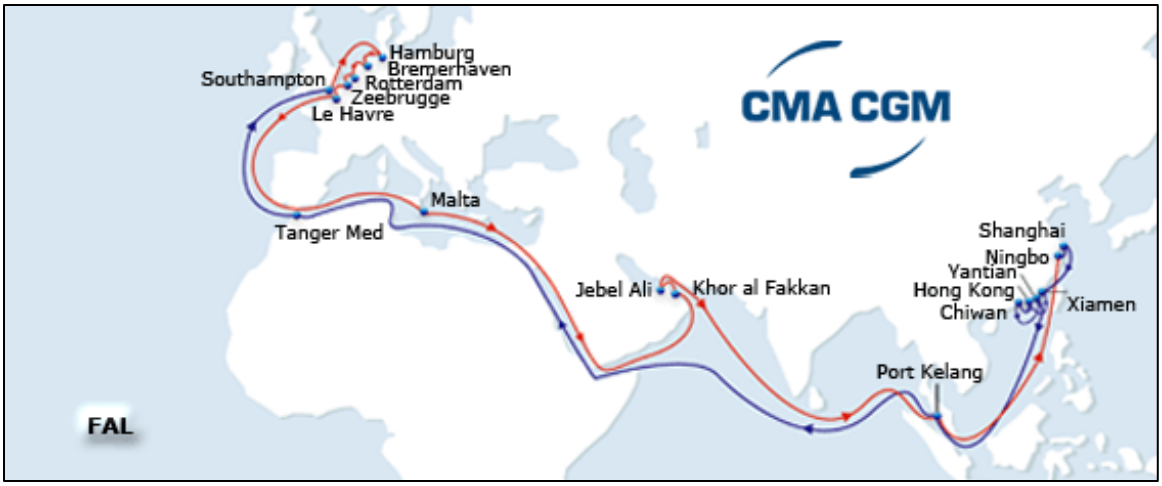


Figure 40. French Asia Line 1 (CMA CGM)[17]

The required numerical data were generated based on the available liner shipping literature and are presented in Table 11. Unit bunker and weekly operating costs were assumed to be 500 USD/ton and 300,000 USD respectively (Wang & Meng, 2012b; Wang et al., 2014). Port waiting cost was set equal to a certain percentage of the weekly operating cost (=40% default value, which may depend on the port of call, vessel characteristics, etc.). Delayed vessel arrival penalties vary from port to port, and were assigned randomly between 5,000 USD/hr. and 6,000 USD/hr. (Zampelli et al., 2014). It is assumed that the liner shipping company cannot deploy more than $q^{max} = 15$ vessels at the given route. The latest start at each port of call was set using the following relationship: $tw_i^l = tw_{i-1}^l + \frac{l_i}{Uniform[v^{max} - v^{min}]}\ \forall i \in I$. The duration of a TW $(tw_i^l - tw_i^e)$ was assigned as uniformly distributed pseudorandom numbers between 24 hrs. and 72 hrs. (OOCL, 2014).

[17] http://www.cma-cgm.com/products-services/line-services/flyer/FAL (accessed on 15 November 2014)

A set of available port handling times p_{is} at each port of call was assigned based on the weekly demand NC_i (in TEUs) and the available handling rates S_i at the given port. Large ports were assumed to have the weekly demand, uniformly distributed between 500 TEUs and 2000 TEUs. Note that term "large port" was applied to those ports of call, if they were included in the list of top 20 world container ports based on their throughput according to the World Shipping Council data[18]. Weekly demand for smaller ports was uniformly distributed between 200 TEUs and 1000 TEUs. Large ports were able to offer 4 possible handling rates: [125; 100; 75; 50] TEUs/hr. Smaller ports could provide either 3 ([100; 75; 50] TEUs/hr.) or 2 handling rates ([75; 50] TEUs/hr.). The latter assumption can be explained by the fact that terminal operators at large ports usually have more vessel handling equipment available and can offer more handling rate options to the liner shipping company. Furthermore, higher amounts of TEU handled can increase productivity.

Table 11
Numerical Data

Bunker consumption coefficients α, γ	$a = 3, \gamma = 0.012$
Unit bunker cost β (USD/ton)	500
Vessel weekly operating cost c^{OC} (USD/week)	300,000
Port waiting cost c^{w} (USD/hr.)	$0.40 \times c^{OC}/168$
Delayed arrival penalty c^{lt} (USD/hr.)	Uniform[5,000; 6,000]
Minimum vessel sailing speed v^{min} (knots)	10
Maximum vessel sailing speed v^{max} (knots)	25
Maximum number of deployed vessels q^{max}	15
TW duration (hrs.)	Uniform[24; 72]

[18] http://www.worldshipping.org/about-the-industry/global-trade/top-50-world-container-ports

The handling cost at each port i under handling rate s was computed as: $sc_{is} = asc \pm Uniform[0; 50]\ \forall i \in I, s \in S_i$, where asc is the average container handling cost. Based on the available literature (Trade Fact of the Week, 2014; TRP, 2014) and assuming a mix of vessel operations that include mooring, loading and discharge of containers, type of container (empty, loaded, size, reefer), re-stowing (on-board the vessel or via quay), the average container handling cost was set equal to [700; 625; 550; 475] USD/TEU for handling rates [125; 100; 75; 50] TEUs/hr. respectively. It was assumed that each terminal operator perceives handling cost differently (i.e., service charge for the same handling rate varies from port to port), which is accounted for by the second (and random) term of the sc_{is} formula.

All numerical experiments were conducted on a Dell T1500 Intel(T) Core i5 Processor with 1.96 GB of RAM. A piecewise linear approximation of the bunker consumption function was performed in MATLAB 2014a. A linearized mixed-integer problem formulation **FDPL** was solved using CPLEX of General Algebraic Modeling System (GAMS[19]).

Bunker consumption function estimation method evaluation. Before assessing potential benefits from the proposed service policy agreement between the liner shipping company and terminal operators, it is necessary to evaluate the suggested bunker consumption function estimation method (AP-2).

[19] http://www.gams.com/

Performance of AP-2 in terms of time complexity and objective function value was evaluated for piecewise linear functions $\overline{G_m^1}(y)$ and $\overline{G_m^2}(y)$, using the numerical data, presented in section "Input data description". A total of 14 instances were generated by varying the number of linear segments m used with each function. Ten replications were performed for each instance to estimate the average computational times. Note that computational time was calculated separately for the following processes: a) Piecewise linear regression in MATLAB 2014a, b) Transfer of the data to GAMS, c) Solving **FDPL** using CPLEX within the GAMS domain, and d) Retrieving the data form GAMS.

The objective function value Z and model accuracy (measured by the coefficient of determination R^2) were recorded for each instance along with the computational time. Changes in the objective function value (referred to as objective gap Δ) with increasing number of linear segments for a given piecewise approximating function were computed for each instance as: $\Delta_{inst} = 100 \times |1 - \frac{Z_{inst}}{Z(m=100)}|$. Results of the analysis are presented in Table 12 for piecewise linear functions $\overline{G_m^1}(y)$ and $\overline{G_m^2}(y)$.

In Table 12 the first and second columns show the instance number and number of segments respectively. The remaining columns present coefficient of determination R^2, objective function value Z, objective gap Δ, and CPU time for each piecewise linear function. For example, when 6 segments are used (see instance 5 in Table 12) in approximations $\overline{G_m^1}(y)$ and $\overline{G_m^2}(y)$, the objective function values at the optimum solution are $Z_1 = 15.22 \times 10^6\ USD$ and $Z_2 = 15.25 \times 10^6\ USD$ respectively.

Table 12
AP-2 Evaluation

Instance	#Segments, m	Piecewise Linear Function $\overline{G_m^1}(y)$				Piecewise Linear Function $\overline{G_m^2}(y)$			
		R_1^2	Z_1, 10^6 USD	Δ_1, %	CPU Time, sec	R_2^2	Z_2, 10^6 USD	Δ_2, %	CPU Time, sec
1	2	0.9783	15.50	3.54	0.24	0.9689	15.71	2.58	0.25
2	3	0.9944	15.54	3.28	0.27	0.9652	15.22	0.62	0.28
3	4	0.9980	15.34	4.50	0.34	0.9731	15.41	0.61	0.32
4	5	0.9991	15.17	5.58	0.35	0.9853	15.22	0.62	0.37
5	6	0.9996	15.22	5.25	0.43	0.9945	15.25	0.43	0.48
6	7	0.9998	15.22	5.26	0.51	0.9950	15.20	0.77	0.55
7	8	0.9999	15.16	5.68	0.60	0.9958	15.17	0.97	0.71
8	9	0.9999	15.60	2.93	0.86	0.9977	15.16	1.07	0.85
9	10	0.9999	15.16	5.64	0.85	0.9961	15.18	0.93	0.86
10	20	1.0000	15.93	0.85	1.30	0.9977	15.80	3.17	1.33
11	40	1.0000	15.95	0.76	3.76	0.9989	16.26	6.15	3.94
12	60	1.0000	16.01	0.37	9.59	0.9997	15.27	0.32	9.50
13	80	1.0000	16.20	0.83	20.94	0.9994	16.13	5.30	21.22
14	100	1.0000	16.07	0.00	37.72	0.9994	15.32	0.00	37.41

For both $\overline{G_m^1}(y)$ and $\overline{G_m^2}(y)$ the objective gap did not exceed 6.15%. As expected, increasing number of segments improved the approximation accuracy (increase in the value of R^2), but increased computational time. However, the computational time increase even for the largest number of segments ($m = 100$) was found to be acceptable (< 38 sec). The piecewise linear function $\overline{G_m^1}(y)$ demonstrated higher accuracy as compared to $\overline{G_m^2}(y)$ and will be further used in numerical experiments. Based on the computational time and the approximation accuracy the number of segments for $\overline{G_m^1}(y)$ will be set to 20.

Input parameter sensitivity analysis. Input parameter sensitivity analysis was conducted for: a) unit bunker cost, b) vessel weekly operating cost, c) port waiting cost, and d) delayed arrival penalty. Next we present results from the sensitivity analysis for each of those input parameters.

Unit bunker cost sensitivity. The main objective of the analysis, presented in this subsection, was to determine how the objective function value will be affected with changing unit bunker cost. From the available literature (Wang & Meng, 2012b) it was found that the unit bunker cost varies from 300 to 1,000 USD/ton. A total of 8 instances were generated by changing the unit bunker cost from 300 to 1,000 USD/ton with an increment of 100 USD/ton. **FPDL** was solved for each one of those instances using the numerical data, presented in section "Input data description". Results of the analysis are shown in Figure 41.

We observe that increasing price of fuel substantially affects the objective function value, and in case of $\beta = 1{,}000$ USD/ton the total bunker cost $BC = \beta \sum_{i \in I}\left(l_i \sum_{k \in K} \overline{G_k}(y_i)\right)$ may comprise up to 30% of the total route service cost.

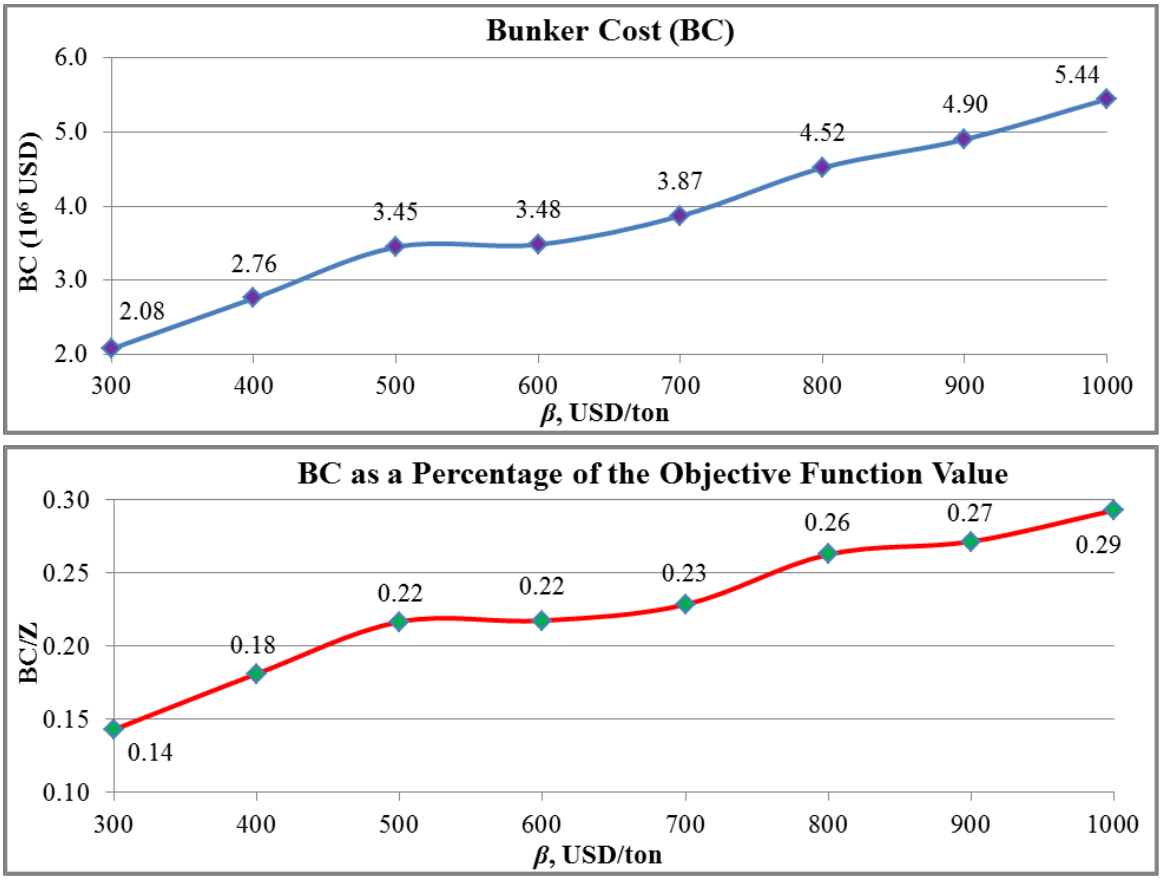


Figure 41 Bunker Cost Sensitivity

Vessel weekly operating cost sensitivity From the available literature it was found that the weekly operating cost depends on the type of vessel and varies roughly from 100,000 to 500,000 USD (Wang & Meng, 2012a-c; Wang et al., 2014). The number of vessels deployed at the given service route is not solely determined by weekly operating costs, as it is also affected by the other **FPDL** decision and auxiliary variables (e.g., bunker cost, port handling cost, port waiting cost, etc.).

In this analysis the number of required vessels was estimated for different combinations of weekly operating and unit bunker costs, while the other input parameters (adopted from Table 11) were assumed to be constant. A total of 72 instances were generated, where the weekly operating cost varied from 100,000 to 500,000 USD with an

increment of 50,000 USD, while the unit bunker cost varied from 300 to 1,000 USD/ton with an increment of 100 USD/ton. **FPDL** was solved for each one of those instances and the number of required vessels for each instance is presented in Figure 42. As expected, increasing unit bunker cost results in the deployment of more vessels (and in the reduction of vessel sailing speed), while increasing weekly operating cost results in the reduction of the deployed vessels (and in the increase of vessel sailing speed). However, for instances with low bunker costs ($\beta < 400$ USD/ton) the number of required vessels was not affected by the weekly operating cost.

Port waiting cost sensitivity. As previously discussed, in some cases a vessel is required to wait at a dedicated area at a given port to ensure feasibility of arrival at the next port of call. In this subsection we explore how the total port waiting time varies with the hourly port waiting time cost. Port waiting time cost was estimated as hourly percentage of the weekly operating cost. A total of 10 instances were generated, where the waiting time cost varied from 5% of the weekly operating cost (i.e., $0.05 \times \frac{c^{oc}}{168} = 0.05 \times \frac{3{,}000{,}000}{168} = 89$ USD/hr.) to 50% of the weekly operating cost (i.e., $0.5 \times \frac{c^{oc}}{168} = 0.05 \times \frac{3{,}000{,}000}{168} = 893$ USD/hr.) with an increment of 5%. **FPDL** was solved for each one of those instances using the numerical data, described in section “Input data description”. Results of the total port waiting time vs. the hourly port waiting time cost from the analysis are presented in Figure 43. From these experiments no obvious pattern emerged between hourly and total port waiting time costs.

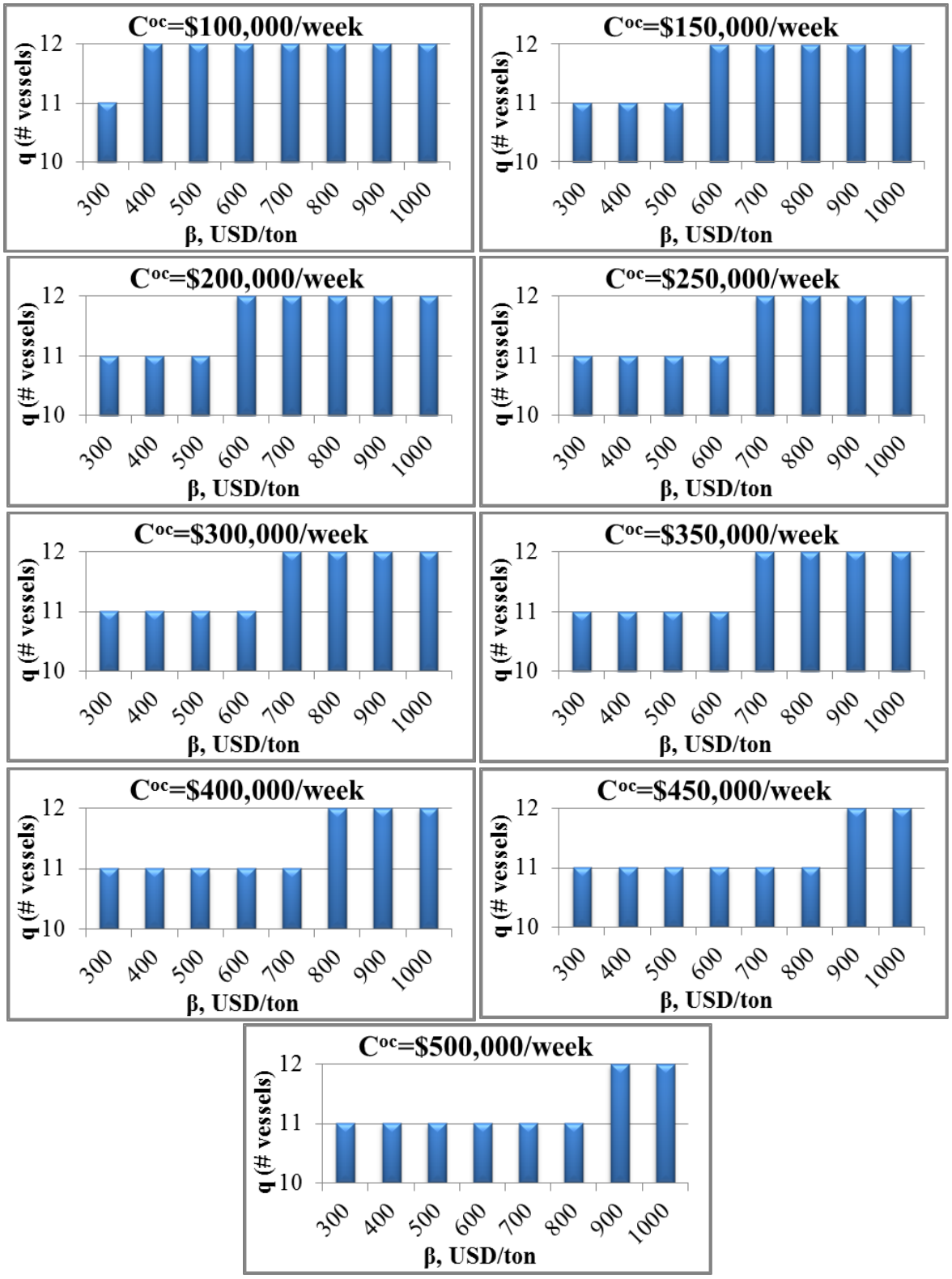


Figure 42. Number of Required Vessels Estimation

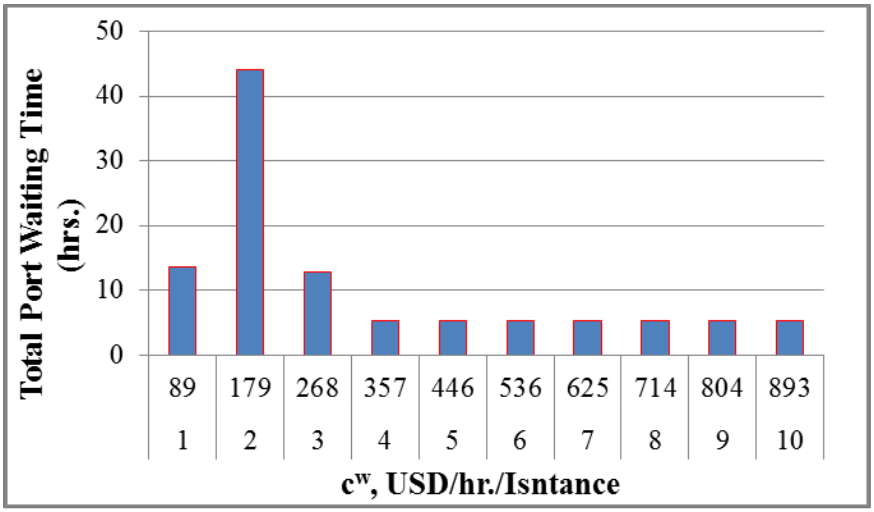


Figure 43. Port Waiting Cost Sensitivity

Delayed arrival penalty sensitivity. The main objective of the analysis presented in this subsection was to identify how late arrivals fluctuate with the delayed arrival penalty value. A total of 8 instances were generated by varying the lower and upper bounds of the uniform distribution, representing the delayed arrival penalty, from Uniform[2,000; 3,000] to Uniform[9,000; 10,000] USD/hr. with an increment of 1,000 USD/hr. **FPDL** was solved for each of those instances using the numerical data, presented in section "Input data description". Results of the analysis are depicted in Figure 44 and indicate that increasing delayed arrival penalty significantly reduces total port late arrivals. For the problem instance with the lowest penalty value (Uniform[2,000; 3,000]) total port late arrivals equal roughly 126 hrs., while for instances with high penalty values Uniform[7,000; 8,000] - Uniform[9,000; 10,000] the total port late arrivals did not exceed ≈50 min. Note that this model does not account for costs to the liner shipping company by the shipper(s) for late arrivals of cargo.

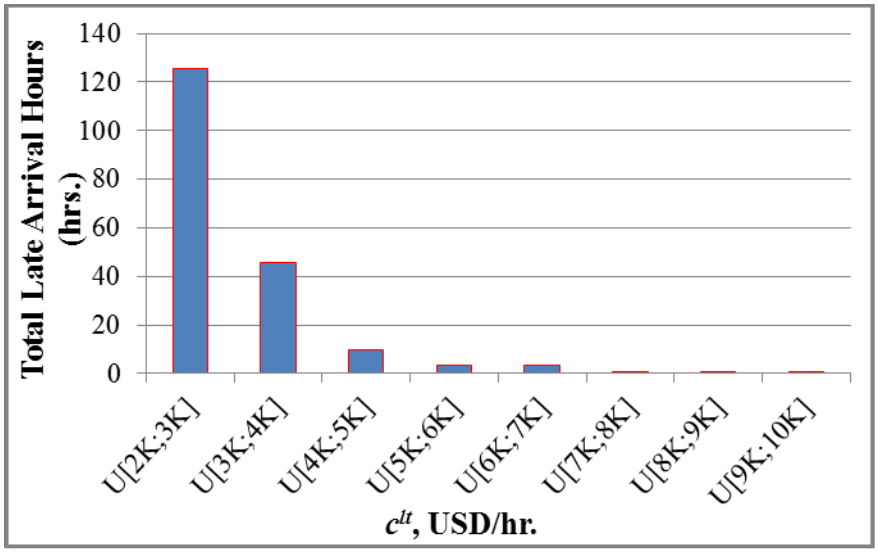


Figure 44. Delayed Arrival Penalty Sensitivity

Service policy agreement evaluation. This section presents computational experiments conducted to quantify efficiency of the proposed service policy agreement. A total of 5 instances were generated by varying the number of available handling rates at each port of cal. All instances are outlined next.

- Instance 1: Large ports have 4 handling rates, smaller ports have 2÷3 handling rates (as described in section 6.1)
- Instance 2: Large ports have 3 handling rates, smaller ports have 2÷3 handling rates
- Instance 3: Large ports have 2 handling rates, smaller ports have 1÷2 handling rates
- Instance 4: Large ports have 1 handling rate, smaller ports have 1÷2 handling rates
- Instance 5: All ports have only one available handling rate.

FPDL was solved for each one of those instances using the numerical data, described in section 6.1. Results, presented in Table 13, include total port handling costs ($PC = \sum_{i \in I} \sum_{s \in S_i} p_{is} x_{is} sc_{is}$) and savings and the objective function value and savings. Savings are estimated as a percentage in PC and Z reduction of the best alternative (instance 1 with the largest amount of available handling rates) as compared to the other alternatives (instances 2 through 5). The highest total port handling cost and the highest total route service cost were recorded for Instance 5, when only one handling rate was available at each port of call. Furthermore, the suggested agreement between liner shipping companies and terminal operators could yield up 35.9% and 14.4% savings for the former in total port handling cost and total route service cost respectively.

Table 13
Service Policy Agreement Evaluation Results

Instance	*PC*, 10^6 USD	*Z*, 10^6 USD	*PC* savings from I1, %	*Z* savings from I1, %
I1	9.1	15.9	0.0	0.0
I2	9.3	16.1	2.2	1.3
I3	9.9	16.4	9.4	3.0
I4	11.6	17.6	27.5	10.6
I5	12.4	18.2	35.9	14.4

Conclusions and Future Research

Taking into account increasing international seaborne trade volumes, liner shipping companies and marine container terminal operators should improve efficiency of their operations in order to serve the growing demand. This study proposed a new service policy agreement between a liner shipping company and several terminal operators, where each terminal operator offers a set of handling rates to the liner shipping

company. The problem was formulated as a mixed integer non-linear mathematical programming model, minimizing the total route service cost for the liner shipping company. The proposed model formulation was linearized and solved using CPLEX within acceptable computational time. Numerical experiments were performed for French Asia Line 1 route, served by CMA CGM liner shipping company. Results demonstrated efficiency of the suggested methodology for estimating the approximated bunker consumption value. Furthermore, it was found that the proposed form of agreement between liner shipping companies and terminal operators could yield up to 14.4% savings in the total route service cost. Future research may focus on the following: a) uncertainty in port handling and sailing times, b) multiple service routes, c) heterogeneous vessel fleet, d) multiple (non-consecutive) service time windows at each port of call, and e) penalties (by shippers) for late arrival of cargo.

6. FLEET DEPLOYMENT PROBLEM WITH UNCERTAIN SAILING SPEEDS AND PORT HANDLING TIMES: A GAME THEORETIC APPROACH

Introduction

As it underlined in the previous chapter, both MCT operators and liner shipping companies have to account for different types of uncertainty in their operations. Drewry Maritime Research mentions that at certain liner shipping routes (e.g., Asia-Europe) only around 60% of the vessels arrive to the ports of call on time (Cargo Business, 2014). Both MCT operators and liner shipping companies have to mitigate negative externalities, caused by uncertainties, and maintain efficiency of their operations. This chapter overviews different approaches for modeling uncertainty in liner shipping with emphasis on vessel sailing and/or port handling times and proposes a new framework, capturing uncertainty in port and liner shipping services, which can be used by a liner shipping company in the development of robust vessel schedules.

Overview of the Relevant Literature

As a result of the literature research it was found that a very few studies focused on modeling uncertainty in liner shipping operations (Wang & Meng, 2012c). A detailed description of those studies was presented in the previous chapter. A summary of relevant studies is outlined in Table 14, including the following: authors, year, modeling port time uncertainty, modeling sailing time uncertainty, solution approach used/notes. Those studies can be divided in the following groups depending on how the uncertainty was captured: 1) assigning statistical distributions for both port and sailing times (Chuang et al., 2010), 2) assigning a statistical distribution to one of the components (either port time or sailing time), while the other component is estimated based on the objective function

and realization of the uncertain parameter (Wang & Meng, 2012a; Wang & Meng, 2012c), and 3) consideration of multiple scenarios for uncertain port and/or sailing times (Brouer et al., 2013; Qi & Song, 2012). Along with studies, described herein, a few researchers considered uncertainty in container demand (Wang et al., 2013; Wang et al., 2014).

Table 14
Overview of the Literature on Uncertainty in Liner Shipping

Authors	**Year**	**Port Time**	**Sailing Time**	**Solution Approach/Notes**
Chuang et al.	2010	Statistical distribution	Statistical distribution	Fuzzy EA. Triangular distributions were assigned to port and sailing times.
Qi & Song	2012	Scenario analysis	Objective	Simulation-based stochastic approximation method. Different levels of port time uncertainty (ranging from U[0,0] to U[0,20] hrs.[20]) were considered.
Wang & Meng	2012a	Statistical distribution	Objective	The original program was reformulated as a linear problem and solved using CPLEX. The port time uncertainty was modeled using uniform distribution, while the sailing time contingency was estimated based on realization of a port time and an additional parameter, denoting hedge against contingency (proportional to length of a voyage leg).
Wang & Meng	2012c	Statistical distribution	Objective	The original problem was linearized and solved using CPLEX. Sample average approximation (SAA) was used to address stochastic port waiting and service times. Uncertainties in port waiting and handling times were modeled using the truncated normal distributions.
Brouer et al. (2013)	2013	Scenario analysis	Scenario analysis	The problem was solved using CPLEX. The following disruptive scenarios were modeled: a) vessel delays due to weather conditions, b) a port closure, c) a berth prioritization, when two vessels arrive simultaneously to the port and are scheduled at the same berth, and d) an expected port congestion.

[20] U[*a*; *b*] denotes uniform distribution with bounds *a* and *b*

Ben-Tal and Nemirovski (1998) outlined the following approaches for modeling uncertainty:

1. ***Post-optimization*** – uncertainty is initially ignored, but once the optimal solution for the problem is found, an additional sensitivity analysis is conducted for uncertain parameters;

2. ***Stochastic Programming*** – uncertainty is assumed to be stochastic in nature, and a specific statistical distribution is assigned to each uncertain parameter;

3. ***Robust Mathematical Programming*** – several scenarios are considered for uncertain parameters. A candidate solution is allowed to violate scenario realization, but violations are penalized.

The first approach does not explicitly capture uncertainty. Ben-Tal and Nemirovski (1998) mentioned that the stochastic programming approach might be problematic, as it is usually quite difficult to derive probabilistic distributions for uncertain parameters (not enough data, errors in fitting the data to a specific statistical distribution, etc.). Scenario analysis may be time consuming depending on the number of scenarios to be considered. This study will model uncertainty via introduction of upper and lower bounds on uncertain parameters (which is an extension of the robust mathematical programming). Such approach was used by several researchers in the past and was found to be efficient (Ben-Tal & Nemirovski, 1998; Golias et al., 2013; Konur & Golias, 2013).

Problem Description

The problem, studied herein, is similar to the one, presented in chapter 5 of this dissertation. A liner shipping company has to provide service for a shipping route, which

includes $I = \{1, \dots, n\}$ ports of call (see Figure 36). Each port should be visited once a week. A given vessel should arrive to each port of call within specific TW. Late arrivals will be penalized (see chapter 5, Figure 37). Weekly demand at each port of call is known. Each terminal operator offers various handling rates to the liner shipping company. Container handling charges increase, if faster vessel service is requested. The vessel has to wait at a given port of call, if it arrives to the next port of call before the earliest TW when sailing at the lowest possible speed (see Figure 37). Assumptions regarding the bunker consumption will be similar to the ones, adopted in chapter 5.

Unlike in chapter 5, vessel sailing speed at each leg and port handling time at each port of call are assumed to be uncertain. As mentioned earlier, this study will use upper and lower bounds for capturing uncertainty of a given parameter. It is assumed that longer legs will have larger difference between upper and lower bounds, because sailing at the desired speed is more uncertain at longer legs as compared to shorter legs. Similarly, faster handling rates will have larger difference between upper and lower bounds, because port handling time is more uncertain under the faster handling rate.

Mathematical Formulation

A mixed integer non-liner mathematical model for the robust fleet deployment problem with uncertain vessel sailing speeds and port handling times **RFDP[1]** is presented next.

Nomenclature

Sets

$I = \{1, \dots, n\}$	set of ports to be visited
$S_i = \{1, \dots, s_i\}$	set of available handling rates[21] at each port $i \in I$

[21] Set of handling rates contains indexes of available handling rates (i.e., if a terminal operator at port i offers two handling rates 75 TEUs/hr. and 50 TEUs/hr., then $S_i = \{1,2\}$)

Decision variables

$x_{is}\ \forall i \in I, s \in S_i$	=1 if handling rate s is selected at port i (=0 otherwise)

Auxiliary variables

q	number of vessels deployed at the given route
$t_i^a\ \forall i \in I$	arrival time to port i (hrs.)
$t_i^d\ \forall i \in I$	departure time from port i (hrs.)
$wt_i\ \forall i \in I$	waiting time of a vessel at port i (hrs.)
$t_i\ \forall i \in I$	vessel sailing time at leg i, connecting ports (i) and $(i+1)$
$f(v_i)\ \forall i \in I$	bunker consumption at leg i when sailing at speed v_i (tons of fuel/nmi)
$lt_i\ \forall i \in I$	vessel late arrival to port i (hrs.)

Parameters

β	unit bunker cost (USD/ton)
c^{OC}	vessel weekly operating cost (USD/week)
c^w	port waiting cost (USD/hr.)
c^{lt}	delayed arrival penalty (USD/hr.)
$l_i\ \forall i \in I$	length of leg i (nmi)
v^{min}	minimum vessel sailing speed (knots)
v^{max}	maximum vessel sailing speed (knots)
q^{max}	maximum number of deployed vessels
$tw_i^e\ \ \forall i \in I$	the earliest start at port i (hrs.)
$tw_i^l\ \forall i \in I$	the latest start at port i (hrs.)
$tc_{is}\ \forall i \in I, s \in S_i$	handling cost at port i under handling rate s (USD)
$\widetilde{\boldsymbol{v}_{\boldsymbol{\iota}}}\ \forall i \in I$	vessel sailing speed at leg i, connecting ports (i) and $(i+1)$
$\widetilde{\boldsymbol{p}_{\boldsymbol{\iota s}}}\ \forall i \in I, s \in S_i$	vessel handling time at port i under handling rate s (hrs.)
$[v_i^u, v_i^l]\ \forall i \in I$	upper and lower bounds on sailing speed at leg i (knots)
$[p_{is}^u, p_{is}^l]\ \forall i \in I, s \in S_i$	upper and lower bounds on vessel handling time at port i under handling rate s (hrs.)

The objective (54) minimizes the total route service cost, which includes 5 components: 1) total vessel weekly operating cost, 2) total bunker consumption cost, 3) total port handling cost, 4) total port waiting cost, and 5) total late arrival penalty.

$$min[c^{OC}q + \beta \sum_{i \in I} l_i f(\widetilde{\boldsymbol{v}_{\boldsymbol{\iota}}}) + \sum_{i \in I} \sum_{s \in S_i} tc_{is} x_{is} + \sum_{i \in I} c^w wt_i + \sum_{i \in I} c^{lt} lt_i] \tag{54}$$

Denote the objective (54) as $Z(q, \widetilde{\boldsymbol{v}}, x, wt, lt)$. Since vessel sailing speeds and port handling times are not known with certainty, the liner shipping company aims to develop

a robust schedule by minimizing the average total route service cost and range of the total route service cost.

RFDP[1]

The objective (55) minimizes the average total route service cost.

$$\min_{v}[\frac{1}{2} \times (\max_{x}\{Z(q, \widetilde{\boldsymbol{v}}, \widetilde{\boldsymbol{x}}, wt, lt)\} + \min_{x}\{Z(q, \widetilde{\boldsymbol{v}}, \widetilde{\boldsymbol{x}}, wt, lt)\})] \tag{55}$$

The objective (56) minimizes range of the total route service cost.

$$\min_{v}[\max_{x}\{Z(q, \widetilde{\boldsymbol{v}}, \widetilde{\boldsymbol{x}}, wt, lt)\} - \min_{x}\{Z(q, \widetilde{\boldsymbol{v}}, \widetilde{\boldsymbol{x}}, wt, lt)\}] \tag{56}$$

Subject to:

Constraints set (57) indicate that only one handling rate can be selected at each port of call.

$$\sum_{s \in S_i} x_{is} = 1 \ \forall i \in I \tag{57}$$

Constraints set (58) define range of a handling time at the port $i \in I$ under service rate $s \in S_i$.

$$p_{is}^{l} \leq \widetilde{\boldsymbol{p}_{\boldsymbol{is}}} \leq p_{is}^{u} \ \forall i \in I, s \in S_i \tag{58}$$

Constraints set (59) calculate a vessel sailing time between ports i and $i + 1$.

$$t_i = \frac{l_i}{\widetilde{\boldsymbol{v}}_{\boldsymbol{i}}} \ \forall i \in I \tag{59}$$

Constraints set (60) ensure that a vessel cannot arrive at the port $i \in I$ before the agreed TW.

$$t_i^a \geq tw_i^e \ \forall i \in I \tag{60}$$

Constraints sets (61) and (62) compute waiting time at the port $i \in I$, necessary to ensure feasibility of arriving to the next port of call.

$$t_i^a + \sum_{s \in S_i}(\widetilde{\boldsymbol{p}_{\boldsymbol{is}}}\, x_{is}) + wt_i + t_i \geq tw_{i+1}^e \; \forall i < |I| \tag{61}$$
$$t_i^a + \sum_{s \in S_i}(\widetilde{\boldsymbol{p}_{\boldsymbol{is}}}\, x_{is}) + wt_i + t_i - 168q \geq tw_1^e \; \forall i = |I| \tag{62}$$

Constraints set (63) calculate a vessel departure time from the port $i \in I$.

$$t_i^d = t_i^a + \sum_{s \in S_i}(\widetilde{\boldsymbol{p}_{\boldsymbol{is}}}\, x_{is}) + wt_i \; \forall i \in I \tag{63}$$

Constraints set (64) estimate hours of late arrival to the port $i \in I$.

$$lt_i \geq \; t_i^a - \; tw_i^l \; \forall i \in I \tag{64}$$

Constraints sets (65) and (66) compute a vessel arrival to the next port of call $i \in I$.

$$t_{i+1}^a = t_i^d + t_i \; \forall i < |I| \tag{65}$$
$$t_1^a = t_i^d + t_i - 168q \; \forall i = |I| \tag{66}$$

Constraints set (67) ensure weekly service frequency (168 denotes the total number of hours in a week). The right-hand-side of an equality estimates the total turnaround time of a vessel at the given route (where the first component is the total sailing time, the second component is the total port handling time, and the third component is the total port waiting time).

$$168q \geq \sum_{i \in I} t_i + \sum_{i \in I} \sum_{s \in S_i} (\widetilde{\boldsymbol{p}_{\boldsymbol{is}}} x_{is}) + \sum_{i \in I} wt_i \tag{67}$$

Constraints set (68) ensure that the number of vessels to be deployed at the given route should not exceed the number of available vessels.

$$q \leq q^{max} \tag{68}$$

Constraints set (69) show that a vessel sailing speed should be within specific limits.

$$v^{min} \leq \widetilde{\boldsymbol{v}_{\boldsymbol{i}}} \leq v^{max} \; \forall i \in I \tag{69}$$

Constraints set (70) define range of a sailing speed at leg $i \in I$.

$$v_i^l \leq \widetilde{\boldsymbol{v}_{\boldsymbol{i}}} \leq v_i^u \; \forall i \in I \tag{70}$$

Constraints (71) – (73) define ranges of parameters and variables.

$$x_{is} \in \{0,1\} \; \forall i \in I, s \in S_i \tag{71}$$

$$q, q^{max} \in N \; \forall i \in I \tag{72}$$

$$\widetilde{\boldsymbol{v}_{\boldsymbol{i}}}, t_i^a, t_i^d, wt_i, t_i, f(v_i), lt_i, \beta, c^{OC}, c^w, c^{lt}, l_i, v^{min}, v^{max}, \widetilde{\boldsymbol{p}_{\boldsymbol{is}}}, tw_i^e, tw_i^l, sc_{is} \in R^+ \; \forall i \in I, s \in S_i \tag{73}$$

Bi-level Model Formulation

Both objective functions (55) and (56) contain two optimization problems (i.e., maximization and minimization of the total route service cost). To overcome this issue we reformulate **RFDP** as a bi-level bi-objective optimization problem **BRFDP**. Denote v_i as a realization of the uncertain vessel sailing speed $\widetilde{\boldsymbol{v}_{\boldsymbol{i}}}$ at leg i, and p_{is} as a realization of the uncertain handling time $\widetilde{\boldsymbol{p}_{\boldsymbol{is}}}$ at port i under handling rate s. Realizations of uncertain vessel sailing speeds and port handling times can be assigned using uniform distribution. Denote $[Q^{MAX}, X^{MAX}, WT^{MAX}, LT^{MAX}]$ and $[Q^{MIN}, X^{MIN}, WT^{MIN}, LT^{MIN}]$ as number of vessels, port handling rate, port waiting time, and hours of late vessel arrivals that maximize and minimize the total route service cost of the given liner shipping schedule for given realizations v_i and p_{is}.

BRFDP[1]

<u>Upper Level:</u>

The objective (74) minimizes the average total route service cost.

$$\min_{v}[\frac{1}{2} \times (\{Z(Q^{MAX}, \widetilde{\boldsymbol{v}}, X^{MAX}, WT^{MAX}, LT^{MAX})\} + \{Z(Q^{MIN}, \widetilde{\boldsymbol{v}}, X^{MIN}, WT^{MIN}, LT^{MIN})\})] \tag{74}$$

The objective (75) minimizes range of the total route service cost.

$$\min_{v}[\{Z(Q^{MAX}, \widetilde{\boldsymbol{v}}, X^{MAX}, WT^{MAX}, LT^{MAX})\} - \{Z(Q^{MIN}, \widetilde{\boldsymbol{v}}, X^{MIN}, WT^{MIN}, LT^{MIN})\}] \tag{75}$$

Subject to:

Constraints sets (57) – (73)

Lower Level:

$$[Q^{MAX}, X^{MAX}, LT^{MAX}, WT^{MAX}] = argmax[\{Z(q, v, \tilde{\boldsymbol{x}}, wt, lt)\}] \quad (76)$$

Subject to:

Constraints sets (57) – (73)

$$[Q^{MIN}, X^{MIN}, LT^{MIN}, WT^{MIN}] = argmin[\{Z(q, v, \tilde{\boldsymbol{x}}, wt, lt)\}] \quad (77)$$

Subject to:

Constraints sets (57) – (73)

Complexity and Solution Algorithm

Bi-level optimization problems are non-convex and difficult to solve using exact optimization algorithms (Golias et al., 2013; Konur & Golias, 2013). A stochastic search algorithm should be developed to solve **BRFDP[1]**. However, lower level problems (76) and (77) can be solved optimally using CPLEX. Despite this fact the future research may focus on the development of efficient heuristics for solving lower level problems faster with acceptable optimality gaps in order to reduce the computational time, required for solving **BRFDP[1]**.

Conclusions and Future Research

The future research may focus on the following: a) design of the solution algorithm for **BRFDP[1]**, b) development of additional heuristics to facilitate convergence of the algorithm, c) conduct numerical experiments for one of the liner shipping routes.

7. CONCLUSIONS AND FUTURE RESEARCH

Maritime transportation plays a very important role for the global trade. The amount of cargos, carried by vessels, increase from year to year. Taking into account international seaborne trade tendencies, MCT operators and liner shipping companies have to improve efficiency of their operations in order to meet the growing demand. This dissertation proposes and models a set of alternatives that can enhance MCT operations and improve efficiency of the liner shipping services. As for MCT operations, it was found that the floaterm concept, when additional QCs were introduced for container handling, substantially reduced the vessel service makespan and improved resilience in case of disruptive events especially for scenarios with significant transshipment volumes. The suggested collaborative agreement between dedicated and multi-user MCT operators, when some of the vessels, arriving for the service to dedicated MCT, could be diverted for the service during specific time windows at a multi-user MCT, resulted in significant total vessel service cost savings.

As for liner shipping services, this dissertation proposes and evaluates a new contractual agreement between liner shipping companies and MCT operators, according to which MCT operators offered various handling rate options to a liner shipping company. The suggested policy yielded substantial total route service cost savings. Besides, the scope of this work included development of the novel framework for capturing uncertainty in liner shipping operations via hierarchical optimization. The future research avenues include the following:

1. Simulation modeling of floaterm MCTs

a) capturing ITV interference

b) implementing optimal ITV deployment strategies

c) accounting for terminal congestion

d) modeling different storage yard strategies and areas for hazmat, overweight, oversized, and refrigerator containers.

2. Berth scheduling at dedicated MCTs with excessive demand

a) cost functions for penalties/premiums based on vessel size and load

b) vessel priorities

c) multiple vessel service per time window

d) adaptive mutation operators to improve solution quality and convergence rates

e) vessel assignment heuristics during mutation.

3. Fleet deployment problem with variable sailing speeds and port handling times

a) apply the proposed methodology for multiple service routes

b) introduce heterogeneous vessel fleet

c) multiple TWs at each port of call

d) late port arrival penalties by shippers.

4. Fleet deployment problem with uncertain sailing speeds and port handling times: a game theoretic approach

a) design of the solution algorithm

b) development of additional heuristics to facilitate convergence of the algorithm

c) conduct numerical experiments for one of the liner shipping routes.

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