Simultaneous-Collaborative Berth, Crane and Yard Allocation Problem:
A simulation study

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Abstract

Berth, quay crane and yard are the main resources of the port that determine the level of service quality provided to shipping lines. In this paper, berth, quay crane and yard allocations are considered simultaneously. Scenarios are made to determine the effect of these factors. The scenario is based on the combination of each level of each factor. Each scenario is simulated to measure the response assessed based on turnaround time. The authors develop a simulation model to investigate the impact of berth, crane, and yard allocation simultaneously. Simulation model was developed to see the impact of simultaneous allocation and collaborative strategy, especially the impact on waiting and turnaround time. The authors develop 16 scenarios from a combination of berth, quay crane, yard and strategy. Author uses two terminals in Jakarta, Indonesia, is the Koja container terminal (TPK Koja) and Jakarta International Container Terminal (JICT). The results show that simultaneous-collaborative allocation can reduce waiting and ship turnaround time. Simultaneous-collaborative strategy reduces waiting time and turnaround time significantly, improving service level to shipping lines.

Keywords: berth allocation problem, uncertain, collaboration.

1. Introduction

Container terminals play a vital role in serving as key nodes in the global container transportation network where intermodal and intra-modal container movements are conducted extensively (Jin, Lee, & Hua, 2015). Container terminal is a complex system involving multiple functional areas and operations. The operations in a container terminal can be classified into the three areas: seaside, yard and landside (Bierwirth & Meisel, 2010)The quay-side area is directly open to container vessels and is equipped with quay cranes for container loading onto and discharging from vessels, while the yard-side area is mainly responsible for container temporary storage where yard cranes and trucks are employed for container stacking and horizontal movement. Various operations, arising at the quay-side area (e.g., berth allocation and quay crane scheduling) and yard-side area (e.g., storage allocation, yard crane scheduling, yard truck scheduling), need to be well organized in order to guarantee the efficiency and competitiveness of the container terminal.

Indicator of port performance one of which is determined based on the length of the ship is in the port (ship turnaround time). Ship turnaround time is influenced by dock allocation, quay crane allocation, and container yard allocation. These factors influence each other, so that the discussion of berth allocation cannot stand alone and involves all three of these factors.

The ship takes time to complete loading and unloading activities. The time is affected by the number of quay cranes allocated to serve the vessel. Each crane has a different level of productivity. Quay cranes take time to perform one cycle of operation. Crane cycle time is the time required to reach the container on the ship, carrying and putting the container on the truck. Truck cycle time is the time it takes the truck to bring the container from the dock to the yard and back to the dock. Truck cycle times are not only determined by distance, but also truck speed and productivity of RTG cranes operating in container yards.

Thus, crane cycle times and truck cycle times must be in sync. If the truck cycle time is greater than the quay crane cycle time, the quay crane must wait until the truck is available. Thus crane performance is not optimal, it affects the overall loading and unloading time.

The allocation of quay cranes also not only takes into account the quantity, but also the position or location of the quay crane. In other words the allocation of quay cranes is determined by where quay crane positions are available and whichever one needs them. Imai 2008 explained that the allocation of QC cannot be done freely. Quay cranes must move on one rail, so the sequence is always fixed and cannot cross each other. As an illustration, the terminal has 3 berths and 8 quay cranes. Berth 1 and 2 are servicing vessels, where berth 1 is allocated 4 quay cranes, berth 2 is allocated 2 quay cranes. The loading-unloading time at dock 2 is longer than the dock 2. In the period t there are two vessel coming and should be serviced, while berth 2 is in operation, while berth 1 and 3 are available. Both vessel require 3 quay cranes each. Berth 1 available for 4 quay cranes, and at berth 3 available for 2 quay cranes. In that condition, the quay cranes located at terminal 1 cannot be allocated directly to berth 3. Allocation can be done by shifting one quay crane from berth 2 to berth 3, and shifting one quay crane from berth 1 to berth 2, and repositioning quay crane located on berth 2. This shift can be done only if allowed for interrupt in terminal 2, if no interrupt is not allowed, then the new shift can be implemented after operation in berth 2 is completed.

Berth, quay crane and container yard are equipment that require huge investment. Therefore, these resources need to be operated efficiently. Inefficient operation can lead to bottlenecks and congestion at the port, which in turn leads to increased waiting times and turnaround time, as well as decreasing service level and port competitiveness.

This paper will discusses a simultaneous berth, quay crane and yard allocation and collaborative strategy. This paper contributes significantly mainly to show the impact of simultaneous-collaborative berth, quay crane, and yard allocation. The rest of this paper is organized as follows. Section 2 has a literature review. Section 3 presents the research methodology. Section 4 results and discussion, section 5 presents discussion and future research.

2. Literature Review

Berth Allocation Problem (BAP) could be either static or dynamic (Imai, Nishimura, & Papadimitriou, 2001). The static BAP (SBAP) assumes all ships to have already arrived at the port when the allocation process begins, whereas the dynamic BAP (DBAP) considers not only ships that have already arrived but also those that will arrive within the planning horizon. Depending on the spatial of the berth, BAP can be classified into two types: discrete and continuous problems (Imai, Sun, Nishimura, & Papadimitriou, 2005; Lalla-ruiz, González-velarde, Melián-batista, & Moreno-vega, 2014). As to the discrete BAP, the quay is partitioned into a number of sections (berths), where one ship could be handled at a time. A vessel cannot moor across a berth boundary and multiple vessels cannot occupy the same berth at the same time. Whereas in the continuous BAP, ships could be served wherever empty spaces are available. Based on the scope of analysis, BAP can be grouped into two: (i) it only discusses the allocation of the berth itself and (ii) it simultaneously addresses allocation of berth and other resources, such as quay cranes and yard. In the simultaneous BAP discussion, coverage can be between berth and quay cranes (berth and crane allocation problem or between berth and yard (berth and yard allocation problem).

The studies focusing on BAP

Initially, the BAP was addressed by using First Come First Service (FCFS) approach. Lai and Shih (1992) conducted a study with the FCFS approach and proposed a heuristic algorithm to assign berths to calling containerships. Similarly Lai and Shih (1992), Brown et al. (1994) also conducted research with the FCFS approach. Observations were carried out in a naval port. An integer programming model was proposed to find the optimal ship-to-berth assignments. They conclude that in order to generate optimal allocation, the vessel is allowed to be shifted to another berth. According to Imai et al. (2001), these conditions cannot be applied to the commercial port, because loading and unloading activities should be done until finish. Imai et al. (1997) conducted a study on the commercial port where most of the allocation of ships was using the FCFS approach. They formulate a static berth allocation problem as a nonlinear integer program to minimize both the total time that the vessels spend at the berth and the degree of dissatisfaction incurred by the berthing order. Based on their research, it was concluded that to obtain optimum services, ways other than the first come first service rule should be explored.

Imai et al. (2001) developed a static approach into a dynamic approach. They formulate a Mixed Integer Programming model. The model is solved using Sub Gradient Lagrangian Relaxation method. However, the proposed solution is still complicated. Imai et al. (2003) developed a model of nonlinear dynamic discrete BAP by adding the priority of scale. The model is solved using Genetic Algorithm. Golias et al. (2009) developed model of discrete and dynamic berth allocation problem and was formulated as a multiobjective combinatorial optimization problem where vessel service is differentiated upon priority agreements. A genetic algorithms based heuristic is developed to solve the resulting problem. Hansen et al. (2008) proposed a variable neighborhood search with the aim to find a solution with minimum total cost that includes the sub-costs of waiting, handling and earliness or tardiness of completion. Xu et al. [32] proposed a heuristic to deal with the DBAP.

The studies focusing on Simultaneous BAP and QCAP

The operations in a container terminal can be classified into the three areas: seaside, yard and landside (Bierwirth & Meisel, 2010) [30]. Among them, the seaside operations are critical due to the use of berths and quay cranes, two scarce resources with significant impacts on a container terminal [17]. In the container terminal seaside, berth allocation problem, quay crane assignment problem and quay crane scheduling problem are three essential seaside operations planning problems and they were often solved separately (Liang, Huang, & Yang, 2009; Raa, Dullaert, & Schaeren, 2011)[18,26,34]. A separate study, however, was found likely to result in poor overall system performance due the neglect on their interrelationships. Thus, seaside operations planning problems have been suggested to be solved in an integrated way (Bierwirth & Meisel, 2010).

The amount of researches on simultaneous berth and QC scheduling problem is relatively small. Park & Kim (2003) first proposed a scheduling method for berth and quay cranes under continuous berth situation. They formulate the MIP model, and a two phased solution procedure was adopted. In first phase berth allocation and rough quay crane allocation was determined, then in second phase detailed crane scheduling was generated considering minimal setups times. Meisel & Bierwirth (2009) investigated a similar problem with the first phase problem in Park & Kim (2003). They applied two metaheuristics, Squeaky Wheel Optimization and Tabu Search, respectively to alter the vessel priority list, and proposed a heuristic for searching better solutions under a given priority list. Their model allow quay cranes can be moved to other vessel before its current vessel finishes processing. Imai et al. (2008) developed a model of simultaneous berth and crane allocation problem with the aim to minimize the total time (waiting and handling time). They formulate the model as an integer modeling and was solved using Genetic Algorithm. Peng-fei and Hai-gui (2008) developed a dynamic simultaneous berth and crane allocation problem with mathematical models, where time of arrival of the vessel and handling time is stochastic. The goal is to minimize the average waiting time. The model is solved using Genetic Algorithm. Zhang et al. (2010) considered the coverage ranges for quay cranes when addressing the simultaneous berth and quay crane scheduling problem under continuous berth situation, and applied a sub-gradient optimization algorithm based on Lagrangian relaxation to search for near-optimal solutions. They solved by a polynomial-time enumeration procedure. Han et al. (2010) developed a model of mixed integer programming in a similar case by adding the priority scale. In this model quay cranes are allowed to move when another dock is performing a loading-unloading operation. Setup time of the crane, as a consequence of quay crane reallocation, is considered in the model. The model is solved using Genetic Algorithm. According to Hsu (2016) almost all these GAs can only support time-invariant QC assignment in which the number of QCs assigned to a ship is unchanged. Hsu (2016) mengembangkan model simultaneous berth dan quay crane allocation dengan penyelesaian menggunakan metode hybrid particle swarm optimization (HPSO), combining an improved PSO with an event-based heuristic. Liang et al. (2009) addressed the dynamic berth allocation process, considering a number of factors, including arrival time, berth location and number of quay cranes. The objective of the problem was to minimize the sum of the handling time, waiting time and the delay time for every ship. A hybrid evolutionary algorithm was proposed to find an approximate solution for the problem. The proposed algorithm was compared to the existing methods and the computational experiments showed that the proposed approaches were more applicable to solve dynamic BAP. Meanwhile, Golias et al. (2014) developed a model by-objective optimization and the model was solved using a heuristic algorithm. Models with constraint non-crossing of quay cranes is developed by Zhihong and Na (2011), solved using Genetic Algorithm. Meanwhile, Liang et al. (2011) developed a model of multi-objective quay crane dynamic allocation problem and berth allocation problem, solved using Hybrid Genetic Algorithm. Chang et al. (2010) discusses the simultaneous dynamic discrete BAP-QCAP using Hybrid Parallel Genetic Algorithm approach (a combination of parallel genetic algorithm with a heuristic algorithm). Raa et al. (2011) developed a model of Mixed Integer Linear Programming by priorities of scale, resolved using Hybrid Heuristic solution procedure.

Giallombardo et al. (2010) developed a model that integrates at the tactical level two decision problems arising in container terminals: the berth allocation problem, which consists of assigning and scheduling incoming ships to berthing positions, and the quay crane assignment problem, which assigns to incoming ships a certain quay crane profile (i.e. number of quay cranes per working shift). They present two formulations: a mixed integer quadratic program and a linearization which reduces to a mixed integer linear program. The objective function aims, on the one hand, to maximize the total value of chosen quay crane profiles and, on the other hand, to minimize the housekeeping costs generated by transshipment flows between ships. They solve the problem using heuristic algorithm which combines tabu search methods and mathematical programming techniques.

Han et al. (2010) mengembangkan model simultan *BAP-QCAP* dengan mempertimbangkan sifat stokastik pada kedatangan kapal dan waktu *handling*. QCs are allowed to move to other berths before finishing processing on currently assigned vessels. The model is solved using genetic algorithm approach. A mixed integer programming model is proposed, and a simulation based Genetic Algorithm (GA) search procedure is applied to generate robust berth and QC schedule proactively.

The studies focusing on BAP and Yard

Berth and crane allocation problem generally aims to minimize the vessels' turnaround time (e.g., Imai et al. 2001; Kim & Moon 2003; Guan & Cheung 2004; Cordeau et al. 2005; Wang & Lim 2007), the berth and yard problem generally focuses more on the resource utilization efficiency and container movement (movement between berth and storage yard). Berth and yard allocation heavily depend on each other. Zhen et al. (2011) developed an integrated model that considers simultaneously the two decision problems with the goal of generating a berth template and a yard template that fit well with each other. Berth template problems are solved first whose results are used as the input of the yard template problem. The result is refined by using an iterative process which is repeated until no improvement is found. The model aim of minimizing the service cost and operation cost.

Hendriks et al. (2013) addressed the integrated berth and yard planning problem by means of an alternating berth and yard planning heuristic approach. They consider as simultaneous berth and yard planning problem with the goal of determining the minimum distance of container shifting from berth to yard and vice versa.

Li and Yip (2013) consider the joint planning for yard storage and berth template in export terminals. Scattered stacking which belongs to cluster strategy is adopted to store clusters in a scattered way. In their work, the berthing positions and the amount of containers in each cluster are first obtained and the exact locations of containers are then derived.

Lee & Jin (2013) developed a simultaneous model of berth and yard for transshipment process with the goal of minimizing the cost of container movement. The problem is formulated as a mixed integer programming model and solved by a memetic heuristic approach. Jin et al. (2015) reformulate the problem in Lee & Jin (2013) as a set covering model and solve it by a column generation approach.

Tao & Lee (2015) addressed a joint planning problem for berth and yard allocation in transshipment terminals. They proposed multi-cluster stacking strategy to split each transshipment flow into a number of container clusters and then stack each cluster in different yard blocks. A mixed integer quadratic programming model is formulated to minimize the total distance of exchanging containers between mother vessels and feeders.

Robenek et al. (2014) Robenek et al. (2014) conducted a simultaneous study of berth and yard by taking problems in bulk terminals. The difference between bulk port and other container terminals is the cargo types on the vessels in a bulk port are various and thus a wide variety of specialized equipment is needed to handle such cargos. An exact algorithm is designed to solve the integrated problem where the master problem is modeled as a set-partition problem and sub problems are solved using mixed integer programming.

3. Research Methodology

We use simulation as research methodology. Simulation is used as an approach to modeling complex systems so that it is difficult to use an analytical model or when the system contains stochastic and uncertain variables (Pujawan et al., 2015). Berth allocation is an NP-hard problem, so the optimal solution is difficult to solve by analytical methods, especially for large entities (Homayouni, Tang, & Motlagh, 2014). Operational activities at ports involving one or more container terminals, which involve the regulation of multiple resources such as quay cranes, rubber tyred gantry, and internal transporters, are categorized as highly complex problems (Abadi, Baphana, &

Ioannou, 2009; Kamrani, Mohsen, Esmaeil, & Golroudbary, 2014; Kia, Shayan, & Ghotb, 2002; Kotachi, Rabadi, & Obeid, 2013).

Simulation methods have been used by some researchers, including models for planning and management systems in ports (Tahar & Hussain, 2013), imitating port operations and estimating performance and outcomes through several scenarios (Kotachi et al., 2013). Kotachi et al. (2013) used a simulation method to analyze multi modal operations at the port. Zeng & Yang (2009) uses a method of integration between simulations with optimization methods to determine loading and discharging schedules in container terminals. Kulak et al. (2013) uses a simulation method to determine strategies to improve long-term container terminal performance by identifying bottlenecks as the cause of inefficient processes, identifying terminal configuration changes in resource allocation, and implementing appropriate strategies to overcome bottlenecks. Tahar & Hussain (2013) conducted a simulation to determine the berthing schedule at Kelang Terminal Container (KTC) with first come first service approach with two priority scenarios based on ship type (mainline, feeder, coastal, ro-ro) and container number.

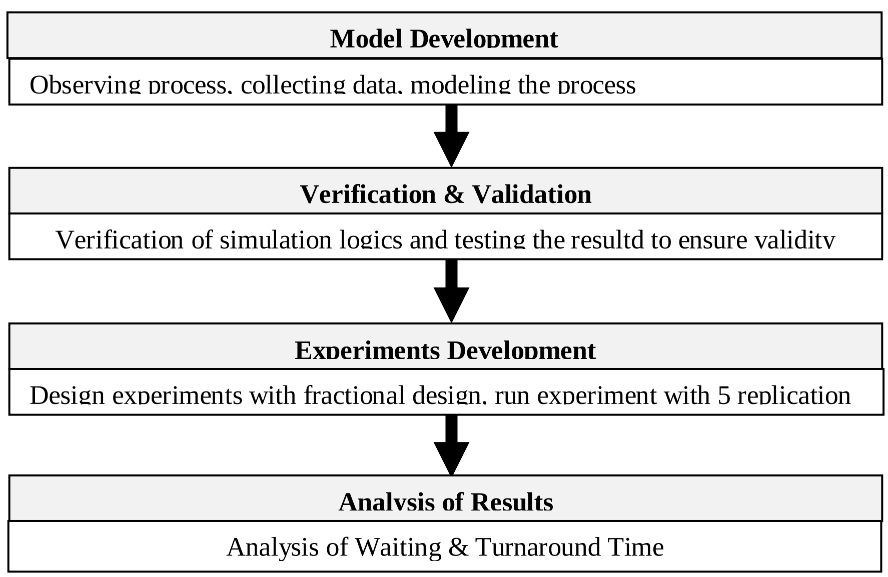

Figure 1. Research Step

Park & Dragovic (2009) used a simulation method to analyze queue and bottleneck problems, container handling, internal transporter, ship schedule, container yard utilization, and port throughput. Kia et al. (2002) used a simulation method to compare the container yard location in the existing port area with a container yard outside the harbor area. Abadi et al. (2009) used a simulation method to determine the effect of ship turnaround and transportation costs due to truck inspection before entering the port. Pujawan et al. (2015) uses a simulation method to integrate delivery planning and silo capacity determination where demand is uncertain. Some researchers use a combination of simulations with analytical methods. Arango et al. (2011) integrate between Genetic Algorithm with simulation (ARENA). Ilati & Sheikholeslami (2014) used a simulation method combined with meta-heuristic.

We adapted the standar simulation methodology in this study (Altiok & Melamed, 2007; Kelton, Sawdoski, & Sawdoski, 2010). Figure 1 shows the four major steps where each will be explained in the following sections. The first is developing the simulation model that started with the observation of real system, understanding the process, and collecting data for input parameters. In any simulation study, it is necessary to ensure that the model reflects the real system and the simulation logics works properly (Kleijnen, 1995; Sargent, 2013). Our second step, therefore, was verification and validation of the simulation model. The third step was running the experiments following the full factorial design with five replications for each treatment. Full factorial is a type of experimental design where all combination of factors are considered (Montgomery, 1997). The experimental results were used to evaluate which factors that have significant impacts on response (waiting time) by the use of analysis of variance (ANOVA). The details of each step will be elaborated in the following sections.

4. Result

Scenario Using Full Factorial Design

In the previous study, berth, quay crane and yard were discussed separately, or discussed by combining one of the factors, eg berth and crane or dock and yard. In this paper, berth, quay crane and yard are considered simultaneously. In this study also added strategic factors.

To see the effect of each factor on the waiting time created a combination of each level of every factor. Table 1 shows four factors where each factor consists of two levels ie low (-1) and high (1). Berth and crane are the factors most often considered in developing the model, among which are done by Y. M. Park & Kim, 2003, Imai, 2008, Peng-fei & Hai-gui, 2008 dan Liang et al., 2009. Zhen et al., (2011), Li & Yip (2013). Lee & Jin (2013) developed the model by considering the relationship between berth and yard.

Table 1. Factors and level

Factors	Number of Level	Level
Service_Order (SO)	2	-1: FCFS 1: Priority
Berth-Yard (B)	2	-1: Flexible 1: Fixed
Crane (C)	2	-1: Fixed 1: Flexible
Strategy (S)	2	-1: Non Collaboration 1: Collaboration

By using full factorial design, it produces a combination of 2 x 2 x 2 x 2 or 16 scenarios. The combination or scenario generated from the four factors can be seen in Table 2. The first combination is a combination of service_order at low level (-1): firs come firs service (FCFS); berth-yard at low level (-1): flexible; crane at low level (-1): fixed and low level strategy (-1): non-collaboration. The first scenario is the current condition (existing condition). The indicator used to measure the response is the waiting time of the ship. Each scenario is simulated using ARENA software with length of replication for one year (365 days) and each combination runs in 5 replications.

Table 2. Scenario

Scenario	SO	B	C	S
1	-1	-1	-1	-1
2	-1	-1	-1	1
3	-1	-1	1	-1
4	-1	-1	1	1
5	-1	1	-1	-1
6	-1	1	-1	1
7	-1	1	1	-1
8	-1	1	1	1
9	1	-1	-1	-1
10	1	-1	-1	1
11	1	-1	1	-1
12	1	-1	1	1
13	1	1	-1	-1
14	1	1	-1	1
15	1	1	1	-1
16	1	1	1	1

Testing Factor Influence Using Anova

The output of the simulation (response) is the waiting time of the ship. The response of the simulation results was processed using the minitab 17 shown in Table 3. The result of the analysis resulted two factors showed significant effect on the waiting time, while the other two factors had no significant effect.

The p-value value of the crane is 0.000, using α of 0.05, it can be said that there is significant influence on how to allocate crane (fixed crane allocation and crane allocation with flexibility) to ship waiting time. The p-value value for the strategy factor is 0.000 and it can be said that the difference in strategy implementation (collaboration and non-collaboration) significantly affects the waiting time of the vessel. The service_order factor has a p-value of 0.390 (p-value> nlai α = 0.05) so it can be said that the servie order of ship has no significant effect to waiting time. Berth_yard factor has a p-value value of 0.184. Thus it can be said that there is no significant influence (berth_yard allocation with flexible or fixed system) to ship waiting time. The p-value of interaction of two factor (crane and strategy) is 0,000, which means that the interaction between the two factors significantly affects the waiting time of the vessel.

Although individual service_order factors have no significant effect on total waiting time, interaction between service_order and crane allocation has significant influence (p-value of 0.022). The p-value of two-factor interaction between service_order and strategy is 0.072. This value is slightly higher than value of α of 0.05. Using α value of 0.05 consistently can be concluded that the interaction between these two factors did not give significant influence to the waiting time. The interaction between service_order and berth_yard, berth_yard and crane, berth_yard and strategy has p-value values of 0.217, 0.284, and 0.972, respectively. These values indicate that there is no interaction between the two factors.

Table 3. Anova for the analysis of the waiting time of the ship

Analysis of Variance					
Source	DF	Adj SS	Adj MS	F-Value	P-Value
Model	15	2689929	179329	37.65	0.000
Linear	4	2272584	568146	119.27	0.000
Service_Order	1	3570	3570	0.75	0.390
Berth_Yard	1	8612	8612	1.81	0.184
Crane	1	586476	586476	123.12	0.000
Strategy	1	1673927	1673927	351.40	0.000
2-Way Interactions	6	371594	61932	13.00	0.000
Service_Order*Berth_Yard	1	7395	7395	1.55	0.217
Service_Order*Crane	1	26254	26254	5.51	0.022
Service_Order*Strategy	1	15931	15931	3.34	0.072
Berth_Yard*Crane	1	5569	5569	1.17	0.284
Berth_Yard*Strategy	1	6	6	0.00	0.972
Crane*Strategy	1	316439	316439	66.43	0.000
3-Way Interactions	4	34024	8506	1.79	0.143
Service_Order*Berth_Yard*Crane	1	30	30	0.01	0.937
Service_Order*Berth_Yard*Strategy	1	15	15	0.00	0.956
Service_Order*Crane*Strategy	1	521	521	0.11	0.742
Berth_Yard*Crane*Strategy	1	33458	33458	7.02	0.010
4-Way Interactions	1	11726	11726	2.46	0.122
Service_Order*Berth_Yard*Crane*Strategy	1	11726	11726	2.46	0.122
Error	64	304868	4764		
Total	79	2994797			

Model Summary			
S	R-sq	R-sq(adj)	R-sq(pred)
69.0186	89.82%	87.43%	84.09%

The p-value of three-factor interaction between berth_yard, crane and strategy is 0.010. It can be concluded that the interaction between these three factors significantly influence the waiting time of the vessel. The interaction of three factors between service_order, berth_yard and crane resulted in a p-value of 0.937. The interaction of three factors between service_order, berth_yard and strategy has a p-value of 0.956. The interaction of three factors between service_order, crane and strategy resulted in a p-value of 0.742. Thus it can be concluded that the interaction between the three factors does not give a significant effect on the waiting time of the ship. The interaction of four factors between service_order, berth_yard, crane and strategy has a p-value of 0.122. Thus, the interaction of these four factors does not have a significant effect on the waiting time of the vessel. The R-square value for the wait time response is 89.82% which means that the changes occurring at the 89.82% waiting time can be explained from the system.

Scenario analysis for waiting time

The analysis is based on the performance of the waiting time of each scenario. Table 4 shows the wait time of 5 replications of each scenario. Scenario 1 on replication 1 resulted in a waiting time of 173.23 hours, in replication 2 resulting in a waiting time of 260.97 hours, with an average waiting time of 192.50 hours. Scenario 2 on replication 1 produces a wait time of 44.18 hours, on replication 2 resulting in a wait time of 25.42 hours, with an average waiting time of 47.03 hours, and so on.

Table 4. Analysis of results based on ship's waiting time

	Waiting Time (hours)					Average
	Replication 1	Replication 2	Replication 3	Replication 4	Replication 5	
Scenario-1	173.23	260.97	164.80	178.15	185.35	192.50
Scenario -2	44.18	25.42	102.97	30.89	31.67	47.03
Scenario -3	666.03	471.42	471.71	408.31	463.81	496.26
Scenario -4	139.53	86.89	118.90	134.36	132.20	122.37
Scenario -5	140.24	146.64	161.53	186.15	154.31	157.77
Scenario -6	22.71	45.31	52.07	34.92	59.34	42.87
Scenario -7	719.69	520.76	457.22	452.38	503.67	530.75
Scenario -8	120.09	96.57	119.53	118.80	148.43	120.68
Scenario -9	174.09	173.71	171.30	274.52	665.23	291.77
Scenario -10	25.45	40.47	25.01	32.16	24.36	29.49
Scenario -11	476.41	430.02	483.51	436.18	508.35	466.89
Scenario -12	95.01	97.67	78.34	82.06	114.33	93.48
Scenario -13	223.27	133.15	189.41	159.43	149.24	170.90
Scenario -14	34.68	44.26	30.02	46.55	41.95	39.49
Scenario -15	561.43	468.60	556.82	455.49	493.47	507.16
Scenario -16	19.36	16.16	19.20	15.71	17.02	17.49

Scenario 1 is a combination of service_order: fisrt come first service; berth_yard: flexible; crane: fixed; strategy: non collaboration resulted in an average waiting time of 192.50 hours. Scenario 2 is a combination of service_order: fisrt cone first service; berth_yard: flexible; crane: fixed; strategy: collaboration resulted in average waiting time of 47.03 hours. The average waiting time decreased from 192.50 hours to 47.03 hours. In the first replication there was a decrease of 129.05 hours, the second replication was reduced by 135.55 hours, and so on. The average decrease of waiting time from scenario 1 to scenario 5 is 145.47 hours.

This result is consistent with anova analysis showing that a non-collaboration strategy change to collaboration will result in a reduction of approximately 351.4 hours. The interaction of two factors between berth_yard and strategy and between crane and strategy resulted in significant effect on ship waiting time. The interaction of three factors between berth_yard, crane and strategy showed significant effect on ship waiting time. Thus the decrease of waiting time of 143.47 hours caused by the main influence of the strategy factor and the influence of interaction between two factors and interaction of three factors.

Scenario 3 is a combination of service_order: fisrt cone first service; berth_yard: flexible; crane: flexible; strategy: non collaboration resulted in average waiting time of 496.26 hours. Based on anova analysis, crane allocation significantly influences waiting time. The interaction of two factors between service_order and crane and between cranes and strategy resulted in a significant effect on the waiting time. The interaction of three factors between berth_yard, crane and strategy also has significant effect on waiting time. Changes in the crane allocation system, the interaction of the two factors and the interaction of the three factors led to an increase in average waiting time of 303.76 hours or from 192.50 hours to 496.26 hours.

Scenario 4 is a combination of service_order: fisrt cone first service; berth_yard: flexible; crane: flexible; strategy: collaboration resulted in average waiting time of 122.37 hours or a decrease of waiting time of 70.13 hours compared with scenario 1. The main influence of crane factor and factor strategy and the influence of two factor interaction between service_order and crane and crane and strategy, and the effect of interaction three factors between berth_yard, crane and strategy cause the waiting time to decrease by 70.13 hours.

Table 5. Comparison of waiting times and existing conditions

	Waiting Time (hours)					Average
Scenario	Replication 1	Replication 2	Replication 3	Replication 4	Replication 5	
Scenario -1	0.00	0.00	0.00	0.00	0.00	0.00
Scenario-2	-129.05	-235.55	-61.83	-147.26	-153.67	-145.47
Scenario-3	492.80	210.45	306.91	230.16	278.46	303.76
Scenario-4	-33.70	-174.08	-45.90	-43.80	-53.15	-70.13
Scenario-5	-32.99	-114.33	-3.28	8.00	-31.04	-34.73
Scenario-6	-150.51	-215.66	-112.74	-143.23	-126.01	-149.63
Scenario-7	546.47	259.79	292.42	274.22	318.33	338.25
Scenario-8	-53.14	-164.39	-45.27	-59.35	-36.92	-71.82
Scenario-9	0.86	-87.26	6.50	96.37	479.88	99.27
Scenario-10	-147.78	-220.50	-139.80	-145.99	-160.99	-163.01
Scenario-11	303.18	169.05	318.70	258.03	323.00	274.39
Scenario-12	-78.22	-163.30	-86.47	-96.09	-71.02	-99.02
Scenario-13	50.04	-127.82	24.61	-18.72	-36.10	-21.60
Scenario-14	-138.55	-216.71	-134.78	-131.61	-143.40	-153.01
Scenario-15	388.20	207.63	392.02	277.34	308.12	314.66
Scenario-16	-153.87	-244.81	-145.60	-162.44	-168.33	-175.01

Scenario 5 is a combination of service_order: fisrt cone first service; berth_yard: fixed; crane: fixed; strategy: non collaboration resulted in an average waiting time of 157.77 hours. Compared to scenario 1 changes occur on berth_yard allocations from flexible to fixed. In the anova table, changes in the allocation system do not have a significant effect on the total waiting time. Significant influence occurred in the interaction of three factors, namely berth_yard, crane and strategy. Decreased average waiting time of 34.73 hours apparantely due to the influence of the interaction between the three factors.

Scenario 6 is a combination of service_order: fisrt cone first service; berth_yard: fixed; crane: fixed; strategy: collaboration produces an average waiting time of 42.87 hrs. Compared to scenario 1 changes occur in berth_yard allocation, crane allocation from flexible to fixed, and strategy change from non collaboration to collaboration. It is clear here that there is a significant influence of the main factors of crane allocation and strategy change. There are significant interactions affecting the waiting time, ie the interaction of two factors and the interaction of three factors. The effect of two factor interaction between service_order and crane and between crane and strategy. The effect of interaction between three factors occurs between berth_yard, crane and strategy. The total effect of scenario 6 resulted in a decreasing wait time of 149.63 hours.

Scenario 7 is a combination of service_order: fisrt cone first service; berth_yard: fixed; crane: flexible; strategy: non collaboration. Compared to scenario 1, changes occur on two factors, namely berth_yard with fixed allocation system and crane allocation system with flexible system. Based on the anova table of berth_yard allocation does not give significant effect to ship waiting time, on the contrary the crane allocation gives significant effect to the waiting time. There are two influences of two factor interactions: service order and crane and crane and strategy. The interaction of three factors between berth_yard, crane and strategy also has a significant effect on waiting time. Total interactions resulted in a wait time change of 530.75 hours, from the previous waiting time of 192.50 or an increase of waiting time to an average of 338.25.

Scenario 8 is a combination of service_order: fisrt cone first service; berth_yard: fixed; crane: flexible; strategy: collaboration. Compared to scenario 1, there are three factors that change ie berth_yard, crane and strategy. Based on the anova table, the main factors have a significant effect on the waiting time, ie cranes and strategy. The interaction of two factors namely service_order and crane and crane and strategy and interaction of three factors between berth_yard, crane and strategy have a significant effect on waiting time. The overall factor influence resulted in decreasing waiting time from 192.50 to 120.68 or an average decrease of 71.82 hours.

Scenario 9-16 is a development of scenario 1-8. In each scenario 1-8 there is a one factor change that is service_order. There is no significant influence of the main factors. Significant influence occurs only in the interaction of two factors between service_order and crane. Thus the total effect that occurs between scenarios 1-8 and 9-16 is almost similar.

Based on the results of the waiting time analysis of scenario 1 to scenario 16 on four factors shows that the main influence of crane and strategy, the influence of two-factor interaction (service_order and crane, crane and strategy), and the influence of three-factor interaction (berth_yard, crane and strategy) shown in Table 4 and Table 5 are consistent with the anova table shown in Table 3.

Determine the best scenario

Each scenario produces different responses on each ship. There is no more dominant scenario than any other scenario. The selection of best scenarios is done gradually. First determine the best scenarios on each ship for each response. The second stage determines the best scenario in aggregate. The best scenario scenario in aggregate is done in two ways, ie determining the highest frequency of each vessel and using the overall average value. Each scenario is compared to scenario 1 which is the existing condition.

Table 6 shows the average waiting time of each scenario, while Table 7 shows the comparative results of each scenario with scenario 1. The best scenario for ship 1 is scenario 10 with average waiting time of 33.33 hours or there is a decrease in waiting time equal to 501.36 hours compared with scenario 1. The best scenario for ship 2 is scenario 10 with waiting time of 33.81 hours. In scenario 10 there is a decrease in waiting time of 430.88 hours compared with scenario 1. From table 7 can be seen that scenario 10 produces the highest frequency. Thus for the wait time response, the best scenario is scenario 10.

Table 6. Analysis of the waiting time of each scenario

	Waiting Time (R1-R5)															
Vessel	S-1	S-2	S-3	S-4	S-5	S-6	S-7	S-8	S-9	S-10	S-11	S-12	S-13	S-14	S-15	S-16
K1	534.69	67.02	1424.14	45.35	473.99	47.26	1540.83	140.90	972.35	33.33	1286.13	104.26	423.36	42.46	1511.12	153.02
K2	464.69	35.80	1416.79	100.47	414.58	42.56	1393.78	118.97	900.36	33.81	1128.26	105.30	445.34	48.76	1247.87	177.36
K3	555.32	44.84	1405.33	87.12	446.85	39.18	1468.11	124.16	901.51	29.45	1133.67	96.03	373.73	48.92	1266.82	167.93
K4	660.39	72.06	1488.99	163.48	559.98	45.43	1814.99	164.43	614.98	39.41	1566.79	139.96	503.12	40.00	1790.57	201.18
K5	454.29	51.98	1396.18	98.69	372.50	60.46	1308.98	102.66	758.19	30.82	1116.67	80.82	454.11	46.88	1312.53	197.44
K6	465.69	29.29	1217.39	82.09	309.96	29.65	1133.07	126.86	757.16	43.12	793.38	64.96	312.01	47.49	1204.26	129.50
K7	411.39	30.90	1155.59	154.02	275.26	47.29	1111.99	113.07	588.95	39.31	1117.28	87.81	304.72	45.22	1164.98	126.52
K8	422.88	50.53	1003.71	135.97	316.85	36.47	1209.59	98.13	612.30	46.56	884.43	55.68	300.65	41.67	920.50	161.73
K9	490.76	33.90	1099.96	141.87	378.53	30.79	1167.49	154.08	769.27	30.90	927.57	66.77	324.75	32.78	1275.29	156.58
K10	296.68	45.07	582.50	173.71	301.40	28.24	792.79	83.37	664.66	28.03	790.16	41.15	229.76	28.69	766.92	104.09
K11	38.23	38.50	95.41	45.35	18.97	22.58	100.02	69.58	29.85	26.73	71.89	76.94	58.11	30.97	82.78	94.62
K12	25.69	26.48	70.72	100.47	34.19	27.91	121.39	87.85	44.82	16.70	98.32	94.30	48.28	47.11	93.15	125.18
K13	3.49	20.56	35.40	87.12	8.31	29.43	57.48	99.19	3.31	9.70	52.79	92.58	15.34	4.45	25.50	98.86
K14	44.60	63.56	192.96	163.48	49.21	48.84	154.61	165.67	75.45	26.30	231.95	99.00	105.05	50.70	158.27	162.31
K15	2.86	17.22	41.46	98.69	3.02	8.93	45.86	68.54	7.92	11.60	45.53	81.37	8.27	8.23	60.72	69.73
K16	40.31	57.37	65.56	82.09	25.72	37.33	148.15	81.45	38.94	27.10	174.82	63.80	58.93	50.33	88.23	112.05
K17	72.73	55.27	160.10	154.02	45.72	63.28	223.05	153.66	102.32	36.93	228.69	116.70	104.93	46.28	202.82	203.22
K18	78.40	47.53	133.32	135.97	44.20	46.53	162.89	143.13	61.79	32.85	159.67	95.19	80.09	41.03	154.02	175.96
K19	59.92	71.65	142.41	141.87	74.85	56.23	200.16	141.42	73.17	57.16	211.91	96.89	117.11	57.52	175.01	168.59
K20	69.31	68.80	136.99	173.71	36.21	37.72	172.94	134.11	36.30	32.60	179.13	126.62	82.43	43.11	118.35	181.70
K21	77.29	72.96	173.61	163.13	58.59	87.78	182.13	153.35	72.89	30.33	200.30	125.58	80.07	43.95	156.57	198.87
K22	39.90	56.20	144.97	113.38	47.37	43.40	108.75	145.37	57.12	23.97	172.65	110.39	84.97	21.72	137.06	160.32
K23	58.82	29.02	65.55	98.09	32.93	55.89	74.87	86.59	44.31	17.15	82.14	85.77	41.50	37.16	93.10	122.35
K24	4.63	12.88	43.82	96.11	11.48	18.48	48.71	75.92	2.71	13.65	35.58	81.26	12.64	7.64	51.82	84.05
K25	40.85	48.13	143.74	147.16	48.20	66.97	108.34	112.63	47.81	19.06	160.55	92.93	72.28	40.09	132.01	134.87
K26	38.14	41.22	126.44	95.62	44.37	50.06	158.15	114.44	60.67	20.36	219.29	99.31	85.26	51.75	146.02	155.78
K27	52.12	25.53	110.86	170.00	29.07	28.05	58.11	156.61	23.66	23.14	71.32	147.47	29.89	21.67	108.86	72.69
K28	53.00	70.07	148.51	109.34	56.81	55.82	155.97	149.00	65.65	31.00	195.21	79.44	97.30	53.73	111.42	187.29
K29	40.83	79.44	169.03	124.04	56.30	50.63	168.38	134.72	72.94	44.09	203.82	102.68	102.19	64.93	151.09	177.31
Average	193.03	47.03	496.26	120.08	157.77	42.87	530.75	120.68	291.77	29.49	466.89	93.48	170.90	39.49	507.16	146.93

Table 7. Comparison of Each Scenario with Scenario 1 (Response: Waiting Time)

	Waiting Time (compare with existing condition (scenario-1))															
Vessel	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
K1	0.00	-467.67	889.45	-489.34	-60.70	-487.43	1006.14	-393.79	437.66	-501.36	751.44	-430.43	-111.33	-492.23	976.43	-381.67
K2	0.00	-428.90	952.09	-364.23	-50.11	-422.14	929.09	-345.73	435.66	-430.88	663.57	-359.39	-19.36	-415.93	783.17	-287.34
K3	0.00	-510.48	850.01	-468.20	-108.47	-516.15	912.79	-431.16	346.19	-525.88	578.35	-459.30	-181.59	-506.40	711.50	-387.39
K4	0.00	-588.32	828.61	-496.90	-100.40	-614.95	1154.61	-495.96	-45.40	-620.98	906.41	-520.42	-157.27	-620.38	1130.18	-459.20
K5	0.00	-402.31	941.90	-355.59	-81.79	-393.83	854.69	-351.63	303.90	-423.47	662.38	-373.47	-0.18	-407.41	858.24	-256.85
K6	0.00	-436.40	751.69	-383.61	-155.74	-436.04	667.38	-338.84	291.46	-422.58	327.68	-400.73	-153.68	-418.21	738.57	-336.20
K7	0.00	-380.50	744.20	-257.37	-136.13	-364.11	700.60	-298.32	177.55	-372.09	705.89	-323.58	-106.67	-366.18	753.58	-284.87
K8	0.00	-372.35	580.82	-286.91	-106.03	-386.41	786.71	-324.76	189.42	-376.33	461.55	-367.21	-122.24	-381.21	497.62	-261.16
K9	0.00	-456.86	609.20	-348.89	-112.23	-459.97	676.74	-336.68	278.51	-459.86	436.82	-423.98	-166.01	-457.97	784.53	-334.18
K10	0.00	-251.62	285.82	-122.97	4.72	-268.44	496.11	-213.32	367.98	-268.65	493.48	-255.53	-66.92	-267.99	470.23	-192.59
K11	0.00	0.27	57.18	7.11	-19.26	-15.65	61.79	31.35	-8.39	-11.50	33.66	38.71	19.88	-7.26	44.55	56.39
K12	0.00	0.79	45.03	74.78	8.51	2.22	95.70	62.16	19.14	-8.99	72.63	68.61	22.59	21.42	67.46	99.49
K13	0.00	17.07	31.91	83.63	4.82	25.94	53.99	95.70	-0.18	6.21	49.30	89.09	11.85	0.96	22.01	95.37
K14	0.00	18.96	148.36	118.88	4.61	4.25	110.01	121.07	30.86	-18.30	187.35	54.40	60.45	6.10	113.67	117.72
K15	0.00	14.35	38.60	95.83	0.15	6.06	43.00	65.68	5.06	8.74	42.67	78.50	5.40	5.37	57.86	66.87
K16	0.00	17.06	25.25	41.78	-14.59	-2.98	107.84	41.14	-1.37	-13.21	134.51	23.49	18.62	10.02	47.92	71.74
K17	0.00	-17.46	87.37	81.29	-27.01	-9.45	150.31	80.93	29.59	-35.81	155.96	43.97	32.20	-26.45	130.09	130.48
K18	0.00	-30.87	54.92	57.57	-34.21	-31.87	84.49	64.73	-16.61	-45.55	81.27	16.79	1.69	-37.37	75.62	97.56
K19	0.00	11.73	82.49	81.95	14.93	-3.70	140.24	81.50	13.25	-2.76	151.98	36.97	57.19	-2.40	115.09	108.67
K20	0.00	-0.51	67.68	104.40	-33.09	-31.59	103.64	64.80	-33.01	-36.71	109.82	57.31	13.12	-26.19	49.05	112.39
K21	0.00	-4.33	96.32	85.85	-18.69	10.50	104.85	76.06	-4.40	-46.96	123.01	48.30	2.78	-33.33	79.29	121.58
K22	0.00	16.30	105.07	73.48	7.47	3.50	68.85	105.47	17.22	-15.93	132.76	70.49	45.08	-18.18	97.17	120.42
K23	0.00	-29.79	6.73	39.27	-25.89	-2.93	16.05	27.77	-14.51	-41.66	23.32	26.96	-17.31	-21.66	34.28	63.53
K24	0.00	8.26	39.19	91.48	6.85	13.85	44.08	71.29	-1.92	9.02	30.95	76.63	8.01	3.01	47.19	79.42
K25	0.00	7.27	102.88	106.31	7.35	26.12	67.49	71.78	6.95	-21.79	119.70	52.08	31.43	-0.76	91.16	94.01
K26	0.00	3.08	88.30	57.48	6.24	11.93	120.01	76.30	22.54	-17.77	181.15	61.17	47.12	13.61	107.89	117.65
K27	0.00	-26.59	58.74	117.88	-23.05	-24.06	5.99	104.49	-28.46	-28.98	19.20	95.35	-22.23	-30.45	56.74	20.57
K28	0.00	17.07	95.51	56.34	3.81	2.82	102.97	96.01	12.65	-22.00	142.21	26.44	44.30	0.74	58.43	134.30
K29	0.00	38.61	128.20	83.21	15.47	9.80	127.55	93.89	32.11	3.26	162.99	61.85	61.36	24.10	110.26	136.48

Turnaround time (comparisons based on best scenarios)

Table 8 shows turnaround time for collaboration and non-collaboration strategies. The vessel 1-10 decreased a very significant ship turnaround time of 343.98 hours, while the 11-29 ships decreased by 25.87 hours. Overall turnaround time decreased by an average of 135.56 hours.

Table 8. Turnaround Time

Turnaround Time					
Vessel	Non Collaboration	Collaboration	Vessel	Non Collaboration	Collaboration
K1	2490.85	2075.75	K16	2090.21	2076.59
K2	1871.35	1552.12	K17	1181.82	1189.26
K3	1607.18	1191.86	K18	1664.20	1529.13
K4	1470.86	894.53	K19	465.07	474.78
K5	1792.48	1458.62	K20	922.61	950.07
K6	1391.33	1004.28	K21	1559.54	1549.66
K7	996.89	616.68	K22	1672.50	1634.35
K8	1309.29	1098.96	K23	2854.79	2542.70
K9	1676.79	1353.78	K24	1337.92	1364.63
K10	2462.26	2382.92	K25	1717.28	1768.29
K11	1604.46	1654.34	K26	587.78	608.56
K12	2396.90	2242.70	K27	784.38	771.79
K13	2187.67	2168.77	K28	1317.47	1260.05
K14	1170.95	1082.39	K29	1000.56	1044.99
K15	1748.19	1859.69			

5. Discussion and Future Research

Based on the waiting time response, it shows that scenario 10 is the best scenario. Scenario 10 is a combination where service_order is a priority; berth_yard allocations are flexible; crane allocation is fixed; strategy used is collaboration strategy. Anova analysis shows that crane allocation and strategy selection have significant individual influence on both response both waiting time and number of waiting vessels. These results reinforce previous research that crane allocation is highly influential on ship waiting time (Han et al., 2010; Liang et al., 2009). Quay cranes are a resource that has significant influence on container terminals (Han et al., 2010; Liang et al., 2009).

The study also confirmed that flexible crane allocations should consider the time for the displacement process so as not to interfere with other cranes that are engaged in loading and unloading activities and propose to use break time to move and consider the time set up of crane displacement (Han et al., 2010). If the break time period is not the same, recalculation is required to recalculate the number of cranes required, especially if the arrival of the vessel does not always occur at the beginning of the working period.

For pairwise comparisons between non-collaboration strategies (scenarios with odd numbers) and collaboration strategies (even-numbered scenarios) then collaboration strategies always deliver better results for both responses. Scenario 2 produces less averages waiting time than scenario 1, scenario 4 produces less averages waiting time than scenario 3, scenario 6 produces less averages waiting time compared to scenario 5, and so on. Comparison of the complete waiting time response can be seen in table 8.

Table 9. Comparison of non collaboration and collaboration

Non Collaboration		collaboration	
Scenario	Waiting Time	Waiting Time	Scenario
Scenario 1	193.03	47.03	Scenario 2
Scenario 3	496.26	120.08	Scenario 4
Scenario 5	157.77	42.87	Scenario 6
Scenario 7	530.75	120.68	Scenario 8
Scenario 9	291.77	29.49	Scenario 10
Scenario 11	466.89	93.48	Scenario 12
Scenario 13	170.90	39.49	Scenario 14
Scenario 15	507.16	146.93	Scenario 16

When comparing simultaneous allocations of berth, yard, and crane, scenarios 3, 7, 9, 11 and 15 produce a larger average waiting time compared to scenario 1. These results are thought to derive from factor and interaction effects between factors such as discussed in sub-section 5.4. In this study, the order of service by using priority is only effective for collaborative strategies. For non-collaboration strategies service priority has no significant effect. In subsequent research it is necessary to consider searching for the order of service with priority systems (M. M. Golias, Boile, & Theofanis, 2010; Han et al., 2010).

Berth_yard no significant impact, both individually and interactions between factors. However, this result can fit up the research conducted by Lee & Jin, (2013), M. P. M. Hendriks et al., (2013) dan Tao & Lee, (2015). Their research is basically aimed at determining minimum transporter movement. The purpose of this study is slightly different from the research they do, that is more to determine the effect of berth_yard allocation to the waiting time.

Berth-yard has a significant influence when interacting with two other factors such as cranes and strategy or service_order and strategy. This is presumably because the distance from the JICT and Koja terminals is relatively short and the speed of the head truck in this model is considered constant.

Another factor is the dwelling time in both terminals which is assumed to be ideal and definite. In this model, if the container yard (inbound and outbound) cannot accommodate the container, the container will be sent to the temporary yard (buffer) to ensure that the conainer yard can hold all containers entering the terminal. In a real system, the actual yard buffer has been applied by put container out of place. For inbound containers, buffer yards typically use temporary yard (TPS) commonly used for overbrengen containers. In subsequent research the influence of yard capacity needs to be considered in more detail and depth.

The collaboration strategy has been initiated by Imai (2008) where the terminal (port) which has limited capacity can perform loading at other docks (ports). With the uncertainty of the arrival of the vessel, which leads to a situation where at the same time there is a surplus and devisit resources simultaneously. In this situation a resource allocation decision is needed that can benefit many parties. Based on the output from scenario 1-16 it can be concluded that collaboration scenario can decrease waiting time. Thus the collaboration will improve service level to shipping lines, reduce the cost of shipping lines and speed up delivery times. Port management becomes more efficient, resulting in increased customer satisfaction that can ultimately improve port competitiveness.

6. REFERENCES

Abadi, A., Baphana, M., & Ioannou, P. (2009). Simulation models for evaluation of terminal operations and traffic flow on adjacent road network. In *12th IFAC Symposium on Transportation Systems* (pp. 129–134).

Altiok, T., & Melamed, B. (2007). *Simulation Modeling and Analysis With Arena*.

Arango, C., Cortés, P., Muñuzuri, J., & Onieva, L. (2011). Berth allocation planning in Seville inland port by simulation and optimisation. *Advanced Engineering Informatics*, *25*(3), 452–461.

Bierwirth, C., & Meisel, F. (2010). A survey of berth allocation and quay crane scheduling problems in container terminals. *European Journal of Operational Research*, *202*(3), 615–627. https://doi.org/10.1016/j.ejor.2009.05.031

Brown, G. G., Lawphongpanich, S., & Thurman, K. P. (1994). Optimizing ship berthing. *Naval Research Logistics*, *41*(1), 1–15.

Chang, D., Jiang, Z., Yan, W., & He, J. (2010). Integrating berth allocation and quay crane assignments. *Transportation Research Part E*, *46*(6), 975–990.

Cordeau, J.-F., Laporte, G., Legato, P., & Moccia, L. (2005). Models and Tabu Search Heuristics for the Berth Allocation Problem, 1–24.

Giallombardo, G., Moccia, L., Salani, M., & Vacca, I. (2010). Modeling and solving the tactical berth allocation problem. *Transportation Research Part B*, *44*(2), 232–245.

Golias, M. M., Boile, M., & Theofanis, S. (2009). Berth scheduling by customer service differentiation : A multi-objective approach. *Transportation Research Part E*, *45*(6), 878–892.

Golias, M. M., Boile, M., & Theofanis, S. (2010). A lamda-optimal based heuristic for the berth scheduling problem. *Transportation Research Part C*, *18*(5), 794–806.

Golias, M., Portal, I., Konur, D., Kaisar, E., & Kolomvos, G. (2014). Robust berth scheduling at marine container terminals via hierarchical optimization. *Computers and Operation Research*, *41*, 412–422.

Guan, Y., & Cheung, R. K. (2004). The berth allocation problem: Models and solution methods. *OR Spectrum*, *26*, 75–92. https://doi.org/10.1007/3-540-26686-0_6

Han, X., Lu, Z., & Xi, L. (2010). A proactive approach for simultaneous berth and quay crane scheduling problem with stochastic arrival and handling time. *European Journal of Operational Research*, *207*(3), 1327–1340.

Hansen, P., Og, C., & Mladenovic, N. (2008). Variable neighborhood search for minimum cost berth allocation. *European Journal of Operational Research*, *191*, 636–649.

Hendriks, M. P. M., Lefeber, E., & Udding, J. T. (2013). Simultaneous berth allocation and yard planning at tactical level. *OR Spectrum*, *35*, 441–456.

Homayouni, S. M., Tang, S. H., & Motlagh, O. (2014). A genetic algorithm for optimization of integrated scheduling of cranes, vehicles, and storage platforms at automated container terminals. *Journal of Computational and Applied Mathematics*, *270*, 545–556.

Hsu, H. (2016). A HPSO for solving dynamic and discrete berth allocation problem and dynamic quay crane assignment problem simultaneously. *Swarm and Evolutionary Computation*, *27*, 156–168. https://doi.org/10.1016/j.swevo.2015.11.002

Ilati, G., & Sheikholeslami, A. (2014). A simulation-base optimization approach for integrated port resource allocation problem. *Trafic and Transportation*, *26*(3), 243–255.

Imai, A. (2008). The simultaneous berth and quay crane allocation problem. *Transportation Research Part E*, *44*, 900–920.

Imai, A., Nagaiwa, K., & Tat, C. W. (1997). Efficient planning of berth allocation for container terminals in Asia. *Journal of Advanced Transportation*, *31*(1), 75–94.

Imai, A., Nishimura, E., & Papadimitriou, S. (2001). The dynamic berth allocation problem for a container port. *Transportation Research Part B*, *35*, 401–417.

Imai, A., Nishimura, E., & Papadimitriou, S. (2003). Berth allocation with service priority. *Transportation Research Part B*, *37*, 437–457.

Imai, A., Nishimura, E., & Papadimitriou, S. (2008). Berthing ships at a multi-user container terminal with a limited quay capacity. *Transportation Research Part E*, *44*, 136–151.

Imai, A., Sun, X., Nishimura, E., & Papadimitriou, S. (2005). Berth allocation in a container port : using a continuous location space approach. *Transportation Research Part B*, *39*, 199–221.

Jin, J. G., Lee, D.-H., & Hua, H. (2015). Tactical berth and yard template design at container transshipment terminals : A column generation based approach. *Transportation Research Part E*, *73*, 168–184.

Kamrani, M., Mohsen, S., Esmaeil, H., & Golroudbary, S. R. (2014). Traffic simulation of two adjacent unsignalized T-junctions during rush hours using Arena software. *Simulation Modelling Practice and Theory*, *49*, 167–179.

Kelton, W. D., Sawdoski, R. P., & Sawdoski, D. A. (2010). *Simulation With Arena* (5th ed.). Mc GrawHill.

Kia, M., Shayan, E., & Ghotb, F. (2002). Investigation of port capacity under a new approach by computer simulation, *42*, 533–540.

Kim, K. H., & Moon, K. C. (2003). Berth scheduling by simulated annealing, *37*, 541–560.

Kotachi, M., Rabadi, G., & Obeid, M. F. (2013). Simulation modeling and analysis of complex port operations with multimodal transportation. *Procedia Computer Science*, *20*, 229–234.

Kulak, O., Polat, O., Gujjula, R., & Gu, H. (2013). Strategies for improving a long-established terminal's performance : a simulation study of a Turkish container terminal. *Flexible Services and Manufacturing Journal*, *25*((2013)), 503–527.

Lai, K. K., & Shih, K. (1992). A study of container berth allocation. *Journal of Advanced Transportation*, *26*(1), 45–60.

Lalla-ruiz, E., González-velarde, J. L., Melián-batista, B., & Moreno-vega, J. M. (2014). Biased random key genetic algorithm for the tactical berth allocation problem. *Applied Soft Computing Journal*, *22*, 60–76.

Lee, D., & Jin, J. G. (2013). Feeder vessel management at container transshipment terminals. *Transportation Research Part E*, *49*(1), 201–216.

Liang, C., Guo, J., & Yang, Y. (2011). Multi-objective hybrid genetic algorithm for quay crane dynamic assignment in berth allocation planning. *Journal of Intelligent Manufacturing*, *22*(3), 471–479. https://doi.org/10.1007/s10845-009-0304-8

Liang, C., Huang, Y., & Yang, Y. (2009). A quay crane dynamic scheduling problem by hybrid evolutionary algorithm for berth allocation planning. *Computers & Industrial Engineering*, *56*(3), 1021–1028.

Meisel, F., & Bierwirth, C. (2009). Heuristics for the integration of crane productivity in the berth allocation problem. *Transportation Research Part E*, *45*(1), 196–209.

Park, N., & Dragovic, B. (2009). A study of container terminal planning. *FME Transactions*, *37*, 203–209.

Park, Y. M., & Kim, K. H. (2003). A scheduling method for Berth and Quay cranes. *OR Spectrum*, *25*, 1–23. https://doi.org/10.1007/3-540-26686-0_7

Peng-fei, Z., & Hai-gui, K. (2008). Study on berth and quay-crane allocation under stochastic environments in container terminal. *Systems Engineering - Theory & Practice*, *28*(1), 161–169.

Pujawan, N., Arief, M. M., Tjahjono, B., & Kritchanchai, D. (2015). An integrated shipment planning and storage capacity decision under uncertainty A simulation study. *International Journal of Physical Distribution & Logistics Management*, *45*(9/10), 913–937. https://doi.org/10.1108/IJPDLM-08-2014-0198

Raa, B., Dullaert, W., & Schaeren, R. Van. (2011). An enriched model for the integrated berth allocation and quay crane assignment problem. *Expert Systems With Applications*, *38*(11), 14136–14147.

Robenek, T., Umang, N., Bierlaire, M., & Ropke, S. (2014). A branch-and-price algorithm to solve the integrated berth allocation and yard assignment problem in bulk ports, *235*, 399–411.

Tahar, R. M., & Hussain, H. (2013). Simulation and analysis for the Kelang Container Terminal operations. *Logistic Information Management*, *13*(1), 14–20.

Tao, Y., & Lee, C. (2015). Joint planning of berth and yard allocation in transshipment terminals using multi-cluster stacking strategy. *Transportation Research Part E*, *83*, 34–50. https://doi.org/10.1016/j.tre.2015.08.005

Wang, F., & Lim, A. (2007). A stochastic beam search for the berth allocation problem. *Decision Support Systems*, *42*(4), 2186–2196. https://doi.org/10.1016/j.dss.2006.06.008

Zhen, L., Hay, L., & Peng, E. (2011). A decision model for berth allocation under uncertainty. *European Journal of Operational Research*, *212*(1), 54–68.

Zhihong, J., & Na, L. (2011). Optimization of Quay Crane Dynamic Scheduling Based on Berth Schedules in Container Terminal. *Joiunal of Transportation Systems Engineering and Information Technology*, *11*(3), 1–6. https://doi.org/10.1016/S1570-6672(10)60123-7