BERTH ALLOCATION PROBLEM UNDER UNCERTAINTY : PRELIMINARY STUDY AT KOJA INTERNATIONAL CONTAINER TERMINAL JAKARTA INDONESIA

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ABSTRACT

The Berth Allocation Problem (BAP) arising in maritime container terminals has received great attention in the literature over recent years. The BAP becomes critically important to the operational efficiency of a container terminal for reducing the total berthing time and cost. It is also an important issue for the operation management in container terminals. Most researchers addressed berth allocation problem at the tactical level in order to achieve the optimal allocation which is used as a basis for making a deal between terminal operators and shipping lines. Shipping lines provide information to the operator terminal that associated with the data required for the loading and unloading. Shipping lines conveying the estimated time of arrival and departure of ships as well as the estimated number of containers discharged/loaded in each period. Results of the negotiations and the agreement are scheduled for the ship visits (ship calls), usually in the form of weekly schedule. Most of the tactical BAP models have used the assumption of deterministic situation where arrival time and number of containers are known in advance. Such a deterministic situation, however, in never occur as a case in real life. Therefore, this paper attempts to show the stochastic behavior of the BAP using Koja International Container Terminals, Jakarta, Indonesia as a case. The results show the stochastic behavior as the difference between the estimated and the actual arrival/departure time of ships as well as the fluctuations and variations in the amount of container loading and unloading in each period.

Keywords: berth allocation problem, uncertain, preliminary study.

1. INTRODUCTION

Berth allocation problem (BAP) is an important issue in the operations of the container terminal. Basically BAP is the allocation of the ship-to-berth so that the vessel can perform loading and unloading activities. 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. BAP is a long-term decision on a tactical level (Legato et al. 2014; Lalla-ruiz et al. 2014). BAP can be considered as an agreement between the operator terminal and shipping company. Although the BAP is a long-term decision, the decision is made based on estimated data, such as estimated time of ship arrival and departure and the estimated number of containers unloaded and loaded. In reality, due to uncertainty of ship movement from point to point the actual arrival and departure often deviates from those initially estimated. Such a deviation creates problems from both ports as well as ship point of view.

According to Wang & Meng (2012), there are two categories of uncertainty related to sea transportation, namely uncertainty at sea and uncertainty in the port. Uncertainty in the sea is causing unpredictability of the vessel arrival time in ports, while the uncertainty in the port causes unpredictability in handling time. Handling time is also affected by the number of containers which may vary from period to period. Several researchers have conducted study related to uncertainty in sea transport. Zhen & Chang (2012) conducted a study to consider the uncertainty of arrival time of the vessel. While Golias et al. (2014) conducted a study taking into account the variability of the number of container. Other researchers consider both, the arrival time uncertainty and variability in number of containers (Zhen 2015; Zhen & Chang 2012; Han et al. 2010). Zhen & Chang (2012) developed two strategies: pro-active and reactive. Proactive strategy is done by adding a buffer time in the initial schedule (schedule generated at the tactical level). While reactive strategy is pursued by making adjustments to the initial schedule.

Li et al. (2015) classify the causes of uncertainty into two groups, namely the uncertainty that occurs repeatedly but ships can still do the loading and unloading, as well as uncertainties which cause the vessel can’t enter and berth in the port. To the uncertainty which causes ships can not enter to the port, Li et al. (2015) proposes to use the strategy of recovery policy by changing the sailing route, while uncertainty that happens repeatedly is suggested to use a proactive strategy. Hendriks et al. (2010) developed a reactive model to address delays in the arrival of the ship which is within the windows by means of relocation quay cranes. Another way is to change the entire schedule. The shift in the schedule of a vessel can cause the risk of disruption of the overall schedule. Some researchers have developed a model to generate the handling time and the waiting time.

This paper will present the results of an empirical study related to uncertainty in sea transport. More specifically we aim to present a data from a container port that shows the uncertainty in the ship arrival and departure. We show the differences between the schedule generated from the tactical level (initial schedule) with the actual ship arrival and departure. The analysis is carried out from two perspectives, namely the terminal operation and the shipping lines. From the viewpoint of the operator terminal the aim is primarily to see the utilization of resources such as berth, quay cranes and yard, while from the standpoint of shipping lines, it is to see the effect of uncertainty on the ship turnaround time. This paper contributes significantly mainly to show the weakness of berth allocation using windows system, particularly in the face of uncertainty of ships arrival time.

The rest of this paper is organized as follows. Section 2 has a literature review. Section 3 provides overview of port operations. Section 4 discusses the uncertainty that occurred in Koja

Container Terminal. Finally, Section 5 concludes this study and suggests some future research directions.

2. LITERATURE REVIEW

Berth Allocation Problem (BAP) could be either static or dynamic (Imai et al. 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 et al. 2005; Lalla-ruiz et al. 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.

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.

Dynamic discrete models focus on the objective of minimizing costs or minimizing the waiting time and the time of loading and unloading operations, as well as the earliest and tardiness costs. Some researchers are looking for methods to resolve berth allocation using different methods such as Lagrangian Relaxation (Monaco & Sammarra 2007), Variable Neighborhood Search (Hansen et al. 2008), Heuristic (Hansen et al. 2008; Xu et al. 2012), Genetic Algorithm (Golias et al. 2009), Lambda Optimal (Golias et al. 2010), Heterogeneous Vehicle Routing Problem with Time Windows (Buhrkal et al. 2011), Hybrid Meta Heuristic (Lalla-Ruiz et al. 2012), Annealing Simulation (Oliveira et al. 2012), Particle Swarm Optimization (Ting et al. 2014). Meanwhile, Imai et al. (2007) developed a model of berth allocation problem with two-objective for the minimization of the total delay time in ship departure and the minimization of the total service time. The model is solved using Sub Gradient Optimization method and Genetic Algorithm. Legato et al. (2014) proposed the concept of BAP integrated between the tactical and operational levels using two separate models where the problem at tactical level was using mathematical programming and the operational level was using the simulation model. Other researchers developed the model by adding other factors such as priority of scale (Imai et al. 2003), a multi-objective (Imai et al. 2007; Golias et al. 2009), variable water depth and tidal condition (Xu et al. 2012). Li et al. (1998) developed a continuous berth allocation as a scheduling problem with multiple jobs on one processor. The model was then solved by using the First-Fit Decreasing Heuristic (FFD Heuristic).

Some researchers focus on integrating berth allocation and crane allocation. 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. 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 DBAP.

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. While 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.

All BAP models presented above have been using the assumption that the arrival of the ship and the operation time is deterministic and known in advance. However, in a real situation, such an assumption may difficult to meet. Li et al. (2015) classify the uncertainties in container transportation into two categories. The first refers to recurring and regular uncertainties such as port congestion, variable terminal productivity, and unexpected waiting time in port channel access (Notteboom 2006). The second refers to rare or one-off eventful uncertainties such as bad weather and labor strikes, which can be termed as disruption events. This type of uncertainties occurs occasionally and irregularly, but it may be partially known sometime before its occurrence. Although this type of uncertainties is rare for a specific vessel at a specific location, the occurrence of such disruption events in the world is not unusual due to the large number of container vessels and their global geographical coverage. Wang & Meng (2012) classified the uncertainties into two categories: uncertainty at sea (adverse weather conditions such as rain, snow, winds, low visibility, tornado, hurricane, and thunderstorm and sea conditions including currents and tides) and uncertainty at port (lack of navigation experience of the ship master; insufficient berth planning system; fluctuation of quay crane handling efficiency; and variation of the number of containers handled in each week). Li et al. (2015) and Wang and Meng (2012) developed classification based on the causes of uncertainty. According to Li et al. (2015), in the event of disruption that causes the ship can not berth, shipping lines can use the strategy of recovery policies by changing the shipping route. These changes are determined by finding the minimal losses on the whole route, as was done by Wang and Meng (2012), differing only at the level of decision, which is on the tactical level.

Zhen & Chang (2012) conducted a study with a focus on proactive strategy, which adds time buffer on the initial schedule. The goal is to anticipate the uncertainty of ships arrival time and the operation time. Their study proposes a bi objective optimization model for minimizing cost and maximizing robustness of schedules. Heuristic method is used to resolve the issue. Zhen et al. (2011) conducted the study on berth allocation problem under uncertain arrival time or operation time of vessels. Their research not only concerns the proactive strategy to develop an initial schedule that incorporates a degree of anticipation of uncertainty during the schedule's execution, but also studies the reactive recovery strategy which adjusts the initial schedule to handle realistic scenarios with minimum penalty cost of deviating from the initial schedule. Zhen (2015) conducted a study to consider the uncertainty of the number of containers that need to be handled. Uncertainty in the number of containers is causing uncertainty in operational time. This study integrates the tactical level to the operational level of berth allocation. The goal of this research is to minimize the deviation of the arrival and departure with the expected arrival time and the expected departure time. They also assume that there is no difference in operating time significantly when the ship is berthing at another berth. They also assume that the number of containers unloaded and loaded are greater than the amount set at the time of signing the contract.

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. Han et al. (2010) developed a model of mixed integer programming in a similar case by adding the priority scale. The model is solved using Genetic Algorithm. Meanwhile, Golias et al. (2014) developed a model by-objective optimization and the model was solved using a heuristic algorithm.

The above literature review showed great concern on the issues of berth allocation particularly that deal with situations of uncertainty. Based on our knowledge there are no authors who does empirical observations to reveal the time difference between scheduled and actual arrival and how it impacts the allocation of the ship. Research needs to be done in a comprehensive and integrated manner between all the factors that affect the ship turnaround time, as well as collaboration between the terminals to utilize the resources of the other terminal.

3. OVERVIEW OF PORT OPERATION

In general, container terminal operations consists of : ship inbound and outbound, quay crane discharging and loading system, internal transportation and container movement, container yard discharging and loading system, stacking system, gate system, inbound and outbound container. Figure 1 illustrates the processes of a terminal operations.

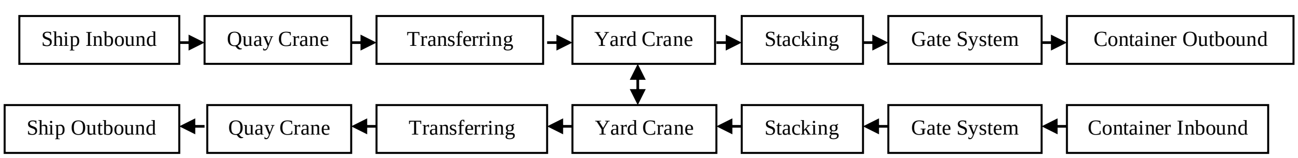

Figure 1. Operation Process at Container Terminals

International container terminal uses ships call system (windows slots), where incoming ships to the terminal are expected to follow a regular schedule. In the ideal events, ships come in the terminal in accordance with a predetermined time. When the ship comes (either as scheduled or not), but berth is not available, then the ship has to wait until the berth is available. After the ship docked, quay cranes allocated to serve the process of loading and unloading. Available quay cranes are allocated according to the needs. Unloading speed is highly dependent on the number quay cranes deployed and their productivity. Quay cranes allocated to each vessel cannot cross each other, because the quay cranes are moving on the same rail.

Import containers are brought into the container yard using internal transporter (truck). The number of trucks that are deployed influence the time of loading and unloading. If the number of trucks that were deployed is less than the number of trucks required, the time period required for unloading becomes greater. The time needed for loading and unloading is also dependent on the distance between the location of berthing and the container yard. When the container arrived at the container yard, rubber tyred gantry (RTG) is used to unload the container. The next process is container stacking. Truck is then back to the berth to take the next container. This process is repeated until the entire import containers are completed. Import containers are subsequently distributed using land transport modes.

Before being transported to the ship, export containers have to be at the terminal started a few days before the ship arrived. Terminal operators will allow time for shipping lines to store the container at the terminal. The time at which shipping lines began stacking process is called "open stack". Each terminal has a different policy towards "open stack". The aim is to avoid congestion at the terminal. The process of loading the export container to the vessel can be made after the entire import containers are completed. In a different way, the loading process undertakes the reverse order of the discharging process.

4. UNCERTAINTY INFLUENCE ON TERMINAL PERFORMANCE

The object of this preliminary study is the Koja Container Terminal (KCT) Jakarta which is the second busiest container terminal in Indonesia under the Jakarta International Container terminal (JICT). Since 2011 the number of loading and unloading reached more than 800 thousand TEUs per year and predicted to continue growing in quantity, as shown in Figure 2. On the other hand, infrastructure and equipment at KCT tend to be quite stagnant. In fact, the function of the equipment tends to decrease, so that the productivity also is decreased. Infrastructure and equipment at the KCT can be seen in Table 1.

Table 1. Facilities and Equipment

Facilities and Equipment	Description
Berth	
Length	650 m
Width	40 m
Draft Channel	-14 m LWS
Draft Wharf	-13 m LWS
Container Yard	
TGS	5700 slot
Area	25,72 Ha
Ground Slot	
Static Capacity for CY Export	7696 TEUs
Static Capacity for CY Import	7560 TEUs
Reefer plug	310 plug
Equipment	
Gate	6 unit
Quay Crane	7 unit
Rubber Tyred Gantry Crane	25 unit
Head Truck	48 unit
Chassis	60 unit

Figure 2. Container Throughput Year 2010-2015.

Table 2. Data Discharging and Loading Koja Container Terminal

Ships Service	Number of Ships Call	Unloading/Loading (TEUS)
APX	30	56.430
ASAL	31	39.212
CAP	41	37.983
ICL	1	177
INE	16	34.275
JSCO2	6	11.974
KIS	11	17279
KPI	29	79.354
KTX-3	31	135.562
PJS2	3	5.772
AD-HOCK	25	2.232
		504.683

Table 2 shows the number of ships call and the amount of container loading and unloading from January to July 2014. Koja Container Terminal has partnerships with the 12 shipping companies. During the period of January to July 2014, the number of ships serviced reached 224 ships call, with the number container loading and unloading reaching 504.683 TEUs. Our observations show that there is a significant time difference between the windows and the actual time of arrival of the ship. The estimated time of arrival (ETA) and estimated time of departure (ETD) of each ship can be seen in Table 3. For example vessel ANX, has berthing slots every Tuesday 18:00-Wednesday 18:00 (42-66), APX every Saturday at 16: 00-Monday at 10:00 (136-178), and so on. The graph shows the ETA and ETD, and actual the time of arrival and departure time as presented in Figure 3. The horizontal axis shows the k^{th} arrival, while the vertical axis shows the k^{th} time of arrival and departure of ships.

Table 3 shows the data of berthing time and the proportion of delays, both late of arrival and departure. Based on the frequency lateness of the arrival, the ANX has been delayed by 68%, APX 61.29%, ASAL 90.23%, CAP 75.61%, INE 87.5%, KPI 84.38% and KTX-3 reaches 100% , while base on the delay of departure, ANX has been delayed by 72%, APX 35.49%, ASAL 80.65%, CAP 65.85%, INE 100%, KPI 84.38% and KTX-3 reaches 93.55%.

Three vessels (ANX, INE, KPI) had an average actual time greater than the time slots available. ANX has a 24 hour time slots while the average berthing reached 28.98 hours, but in case of delay it could increase up to 56.2 hours. Average berthing time of vessels INE is 32.78 hours while slot time is only 22 hours. Slots time for vessel KPI is 30 hours, while the average actual berthing time reached 38.39 hours. Vessel ANX has the highest delay time which is 125.9 hours, or delayed for more than five days, while vessel APX has an average delay time of 46.68 hours. Delay data of the departure also show that vessel ANX is the highest, reaching 137.5 hours. INE had an average delay time of departure of 57.9 hours. The detailed time delays in the arrival and departure of each vessel can be seen in Table 3.

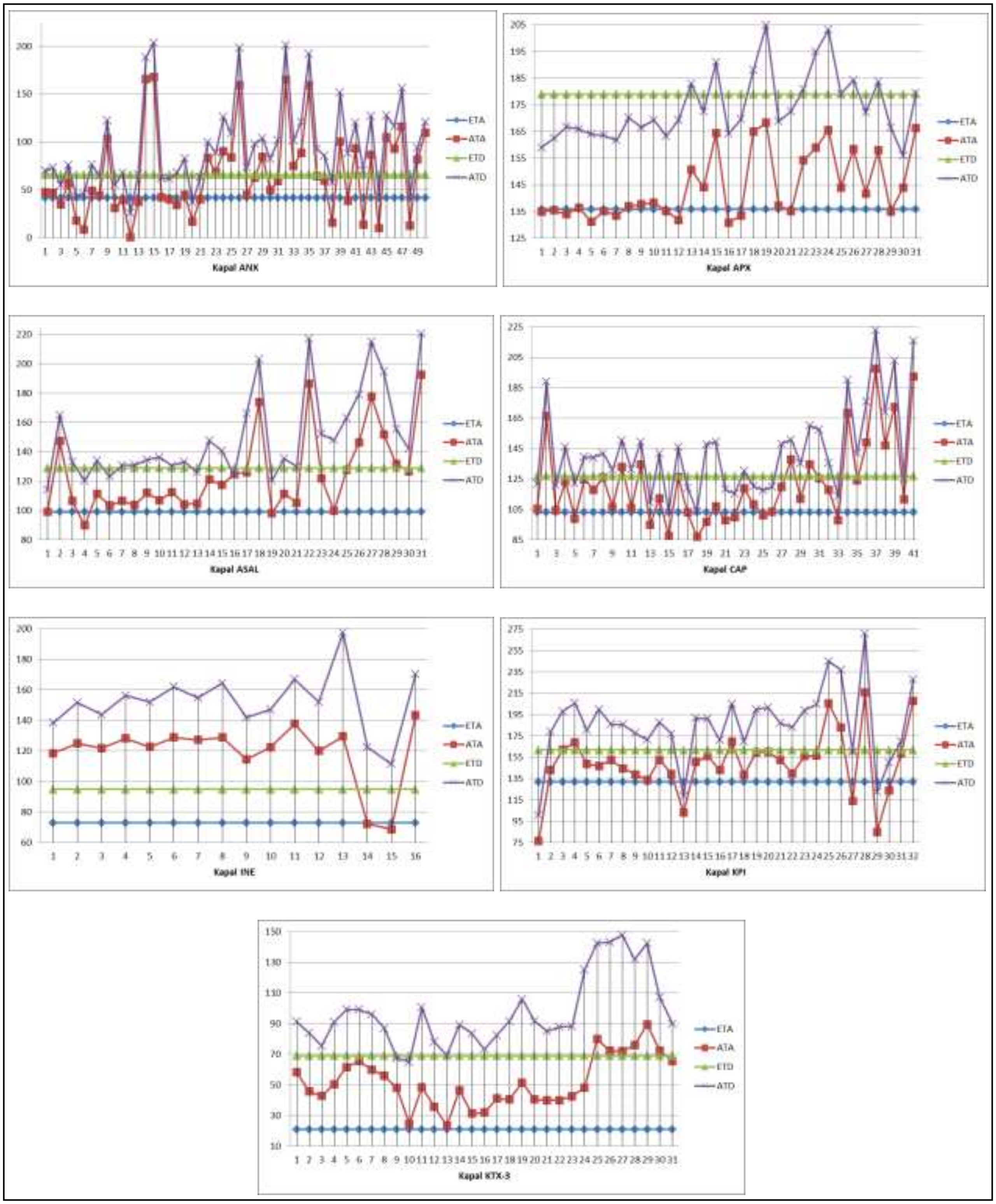

Figure 3. Variability Ship Arrival

Table 3. Estimate and Actual Berthing Time

Ship Service	ETA	ETD	Slot (hours)	Berthing Duration			Late of Arrival			Late of Departure		
				Min	Max	Ave	Max	Ave	Freq (%)	Max	Ave	Freq (%)
ANX	Tue 18:00 (42)	Wed 18:00 (66)	24	11,00	56,20	28,98	125,90	30,56	68,00	137,50	30,02	72,00
APX	Sat 16:00 (136)	Mon 10:00 (178)	43	12,00	49,80	30,10	32,27	9,25	61,29	26,00	3,35	35,49
ASAL	Fri 03:00 (99)	Sat 09:00 (129)	30	5,50	42,60	26,19	93,60	25,49	90,32	91,50	22,99	80,65
CAP	Fri 07:00 (103)	Sat 07:00 (127)	24	11,53	50,95	20,59	94,50	20,56	75,61	96,00	19,77	65,85
INE	Thu 01.00 (73)	Thu 23:00 (95)	22	20,00	68,00	32,78	70,50	46,68	87,50	02,50	57,09	100,00
KPI	Sat 12:00 (132)	Sun 18:00 (162)	30	15,50	55,20	38,39	83,80	22,48	84,38	109,00	29,07	84,38
KTX-3	Mon 21:00 (21)	Wed 21:00 (69)	48	24,40	77,10	46,28	68,50	30,72	100,00	79,00	28,40	93,55

5. DISCUSSION AND FUTURE RESEARCH

Based on the data presented above, it clearly shows that despite the ship has a schedule of arrival and departure, the actual ship's arrival time is uncertain (Wang & Meng 2012). Some studies related to the uncertainty of the ship arrival have been done by previous researchers. Zhen & Chang (2012) conducted a study to address the uncertainties by determining the time of allowances (buffer time). However it will only increase the time allowance and only cover a delay that is "within the windows". Conversely, if the average time of berthing is smaller than the planned duration, the additional allowance time will increase and the resources are idle. Such cases are demonstrated by four ships, namely APX, ASAL, CAP and KTX-3. Allowance time needs to be determined precisely so as not to increase idle time of resources. Zhen et al. (2011) conducted a study to develop a model that has been developed by Kim & Moon (2003). The study aims to minimize tardiness or waiting time on a static berth allocation model. Until now, models of stochastic dynamic berth allocation problem have not been studied.

Besides the uncertainty of the arrival, the number of container loading and unloading of each period is also uncertain. Zhen (2015) conducted a study with regard to the effect of the amount of container to the ship turnaround time. According Zhen (2015) the number of containers in each period are uncertain and stochastic. But a study conducted by Zhen (2015) only shows the variation of the time it takes for the ship to turnaround in each period.

Berthing time is also affected by other factors such as the number of trucks deployed, the speed of transportation, distance from the berth to the container yard, as well as the number and productivity of the quay crane. These factors have not been addressed in a study conducted by Zhen et al. (2011), Zhen & Chang (2012), and Zhen (2015).

Basically, berth allocation problems deal with assigning and scheduling ships to berthing positions, i.e. deciding where and when the ships should moor. There are many factors that influence the berth allocation decisions and these factors influence each other. Uncertainty of ship arrivals and variability in the number of containers carried by each vessel made the allocation problems complex. The studies on berth allocation problems often simplify the above complexity, neglecting the uncertainty nature of the ship arrival and departure and not taking into account variability in the number of containers as well as number of cranes used for loading and unloading. Most analytical models are not flexible enough to address those various complexities.

Based on the above discussion, in order to help overcome the problems of uncertainty, there is a need to develop a model that takes into account these factors. The models were developed to overcome the limitations of available resources. Under conditions of uncertainty, if there are two terminals that operate independently, at the same time, it can happen where the terminals have excess resources which lead to idle, while the other terminal suffered a shortage of resources which leads to prolonged waiting time. Therefore, collaboration between terminals is expected to improve services and improve capacity utilization.

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