AN INTEGRATED SHIPMENT PLANNING AND STORAGE CAPACITY DECISION UNDER UNCERTAINTY: A SIMULATION STUDY

Purpose:

In transportation and distribution systems, the shipment decisions, fleet capacity, and storage capacity are interrelated in a complex way, especially when we take into account uncertainty of the demand rate and shipment lead time. While shipment planning is tactical or operational in nature, increasing storage capacity often requires top management's authority. This paper presents a new way to integrate both operational and strategic decision parameters, namely shipment planning and storage capacity decision under uncertainty. The ultimate goal is to provide a near optimal solution that leads to a striking balance between the total logistics costs and product availability, critical in maritime logistics of bulk shipment of commodity items.

Design / Methodology:

We use simulation as research method. We develop a simulation model to investigate the effects of various factors on costs and service levels of a distribution system. The model mimics the transportation and distribution problems of bulk cement in a major cement company in Indonesia consisting of a silo at the port of origin, two silos at two ports of destination, and a number of ships that transport the bulk cement. We develop a number of 'what-if' scenarios by varying the storage capacity at the port of origin as well as at the ports of destinations, number of ships operated, operating hours of ports, and dispatching rules for the ships. Each scenario is evaluated in terms of costs and service level. A full factorial experiment has been conducted and ANOVA has been used to analyze the results.

Findings:

The results suggest that the number of ships deployed, silo capacity, working hours of ports, and the dispatching rules of ships significantly affect both total costs and service level. Interestingly, operating fewer ships enables the company to achieve almost the same service level and gaining substantial cost savings if constraints in other part of the system are alleviated, i.e., storage capacities and working hours of ports are extended.

Practical Implications:

Cost is a competitive factor for bulk items like cement, and thus the proposed scenarios could be implemented by the company to substantially reduce the transportation and distribution costs. Alleviating storage capacity constraint is obviously an idea that needs to be considered when optimizing shipment planning alone could not give significant improvements.

Originality / Value:

Existing research has so far focused on the optimization of shipment planning/scheduling, and considers shipment planning/scheduling as the objective function whilst treating the storage capacity as constraints. Our simulation model enables 'what-if' analyses to be performed and has overcome the difficulties and impracticalities of analytical methods especially when the system incorporates

stochastic variables exhibited in our case example. The use of efficient frontier analysis for analyzing the simulation results is a novel idea which has been proven to be effective in screening non-dominated solutions. This has provided us with near optimal solutions to trade-off logistics costs and service levels (availability), with minimal experimentation times.

Keywords: *shipment planning, storage capacity, uncertainty, simulation, transportation, efficient frontier*

Introduction

Reducing logistics costs has been a major issue in many industries, especially those dealing with relatively low value commodities such as construction materials, cement, fertilizer and oil, where the logistics costs could make up a substantial percentage of the total cost of goods sold. One way of reducing this cost is by improving the efficiency of the transportation and distribution processes that ultimately achieve better economies of scale. This is fulfilled, for instance, by moving them in bulks using large-scale transporters, often by the use of maritime line operations (Al-Khayyal & Hwang, 2007; Christiansen *et al.*, 2011; Dauzère-Pérès *et al.*, 2007; Siswanto *et al.*, 2011) and then stored them in large quantity (Christiansen *et al.*, 2011; Pantuso *et al.*, 2014) using large tanks or silos.

While reducing transportation cost is important, it is equally critical to maintain high product availability in the market. Stock-outs could result in customer dissatisfaction and in the long run could cost the company in terms of losing the market share. The trade-off between product availability and transportation cost in the context of low value goods transported via maritime lines is known to be a hard and complex problem due to its low visibility, high uncertainties and long delay (Christiansen *et al.*, 2006; Christiansen *et al.*, 2013; Panayides, 2006).

Both logistics costs and product availability are affected by shipment planning and storage capacity. Shipment planning deals with decisions of which items or which ship to depart from the point of origin to the point of destination. There is a large body of literature discussing shipment planning and scheduling, most of them are in the area of optimization. Persson and Göthe-Lundgren (2005), for example, presented a model of shipment planning of oil from refineries to depot. Christiansen *et al.*, (2011) developed model and solution procedure for shipment planning of multi-product cement from producing factory to regional silos. Some other publications integrated shipment planning or scheduling with other decisions. For example, some authors integrated routing decisions with inventory decisions (for example, Coelho *et al.*, 2012; Song & Furman, 2014).

There is a strong interplay between shipment planning and storage capacity decisions in the logistics of bulk items. However, the influence of storage capacity in shipment planning is recognized in only a few earlier studies. Stacey *et al.* (2007) suggest that storage space clearly has a significant effect on both the routing and inventory decisions in the context of inbound transportation. In the maritime transportation of bulk items, such interplay is even more evident. If a ship is dispatched too late, then there could be an out-of-stock

situation at the destination. Conversely, if dispatched too early, then the ship could arrive when the silo is unavailable (full or almost full), which prevents the unloading process to commence immediately after the ship arrives resulting in lower ship utilization and higher shipping costs. The problems is further exacerbated by the uncertainty of the docks' availability and schedules of other ships arriving at the same ports, problems with weather that may affect the unloading process and the limited working hours at the ports (i.e., some ports are not working 24 hours a day).

In such a circumstance, the critical decision is not only about obtaining the 'best' schedules of ship departure from the port of origin, but also to determine the appropriate capacity of storage at the port of origin as well as ports of destination. Small storage is generally cheaper to build and operate, but it may lower the ship productivity because ships often have to wait for unloading. Service level may also be affected as silo capacity is directly related to the ability to maintain the buffer stock. As pointed out by Ronen (2002), in the maritime transportation, inventory and storage at both ends should be taken into account. At the port of origin, smooth production needs to be ensured, and equally, at the port of destination, the bottleneck due to the inadequate capacity of the storage that potentially disrupts the unloading process has to be minimized.

Shipping decisions are typically tactical or operational in nature, and deal with issues such as determining the number of ships to operate and the dispatching rules of the ships. Decisions about storage capacity, on the other hand, tend to be strategic in nature (Manzini and Bindi, 2009) as they involve large capital investments (Ronen, 2002) and usually require the authority of the board of directors, and trading-off the two decisions under uncertainty (distinctive in bulk shipment of commodity items) is challenging.

While a large body of literature has been discussing about shipment planning and ship scheduling, there are at least two major issues that require further attentions. *First*, the majority of publications addressing the maritime transportation problems (see for example Ronen, 2002; Dauzère-Pérès *et al*., 2007; Siswanto *et al*., 2011; Natarajarathinam *et al*., 2012) deal with ship planning or scheduling, while treating the storage capacities (merely) as constraints. This is in contrast to our premise that decisions about shipment planning and capacity decision should be integrated. *Second*, most of the optimization models related to shipment planning and ship scheduling consider deterministic situation. In reality, these decisions are complex and characterized by highly uncertain situation and hence, a model that is able to handle uncertainties related to demand, travel times, and operations at ports is necessary.

Our research is an attempt to fill the above gaps by presenting a model that integrates shipment planning and storage capacity decisions under uncertainty that will lead to a striking balance between the costs and product availability, critical in maritime logistics of bulk shipment of commodity items. We chose the simulation study as a research method based on a premise that simulation is a worthwhile, proven technique to assess various design alternatives especially when the system to be analyzed is operating in a highly uncertain environment (Teixeira *et al.*, 2012) and when analytical techniques are difficult to implement especially if the system incorporates stochastic variables (exhibited in our case example). The simulation model is a representation of a cement producer in Indonesia and the research problems addressed in this paper is motivated by the issues they encountered in the maritime transportation and physical distributions of bulk cement. Although industry-specific, this type of problem structure is representative in other industries such as oil, fertilizer, and other bulk items, which will somewhat lead to a generic research insight.

System Description

Indonesia is a very complex country in terms of logistics and transportation. With over 17000 islands, total territorial area of about 5.19 millions square kilometers and sea makes up about 2/3 of the territorial area, the maritime transports are obviously a vital mode for Indonesian logistics. There is a huge challenge in managing transportation and logistics in Indonesia not only because the country is complex geographically but also because of the poor logistical infrastructure (Russ *et al.*, 2005; de Souza *et al.*, 2007). Long delay in ports is one of the major components of the transportation costs. Our anecdotal observations in Indonesian context suggest that in maritime transport, the percentage of delay and waiting time could be somewhere between 40% - 60% of the ship cycle time.

In this study, we have selected a large cement company in Indonesia as a reference case for developing our simulation model. The choice was based on the fact that this company is one of the largest enterprises in Indonesia and the problems we incorporate in the simulation model could exist in many other companies, especially those handling bulk items.

The company that we model in this study produces cement to serve vast market across the Indonesian archipelago. The products are distributed in the form of packages or bulk. The bulk cement is transported by ships from the port of origin which is located within the

vicinity of the plant, hereby referred to as Port A, to the two ports of destination, called Port B and Port C respectively. Before loaded onto the ship, the bulk cement is first stored in a silo. The loading rate at Port A is about 400 tons per hour and the working hour is typically between 7 am to 7 pm or 12 hours a day.

Port B and Port C have one 11,000-ton silo each. Upon arrival, the ship will unload the bulk cement onto the silo with a rate of 300 tons per hour. Each silo will serve the demand from the local distributors and retailers in the area covered by the packing plant. The packing plant packs the bulk cement into 40-kg or 50-kg sacks. Daily demand is stochastic following a certain probability distribution. From the historical data, the demand of the packing plant in Port B is significantly lower than that of Port C. As the unloading rate could be higher than the demand rate, it is important to have enough space inside the silo at the time the unloading commences to ensure the cement can be completely unloaded from the ship.

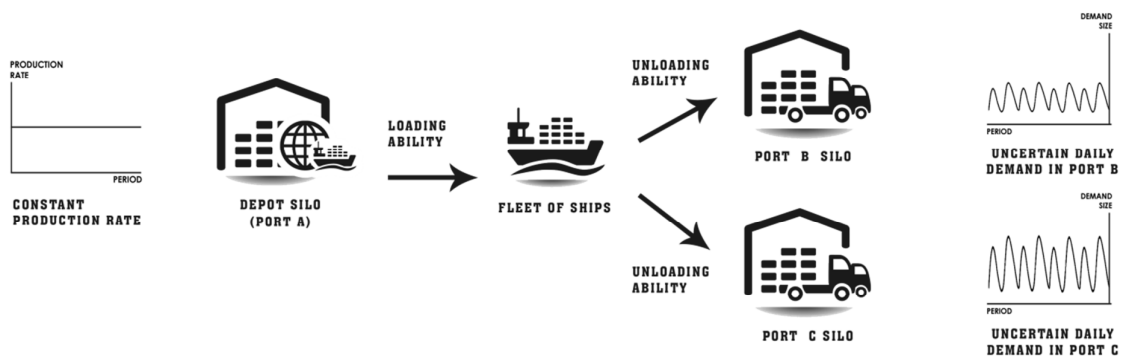Figure 1 illustrates the configuration of the logistics system.

Figure 1. Logistics system configuration.

When a ship arrives at the port of destination, there are a number of possibilities that may occur. First, the ship may directly unload its consignment if (i) the inventory in the silo is below a certain level; (ii) at least one unloading dock is available; and (iii) no weather-related problems that might prevent the unloading process. If any of these conditions is not met, the ship has to wait until all constraints are relieved. From our field study, waiting time has been a major part of the time spent by the vessels. In this specific case, the percentage of waiting time throughout the movement cycle is about 60% to 70% of the total vessel time.

To deliver the product, the company currently charters six heterogeneous ships under the time-charter scheme, each with different chartering rate and capacity. Because the

company charters ships based on time, deciding the departure time is not considered as a major problem by the company; as long as ship is available, they will load the cement and the ship immediately departs to the port of destination irrespective of the inventory on hand and in transit toward the port of destination. However, although incurring almost the same demurrage cost to the company wherever it happens, from the perspective of flexibility, waiting at the port of origin is probably better than at the ports of destination.

In our scenario, we take into account the on-hand inventory and in-transit inventory when deciding the departure time of a ship. This is done by setting up a point of inventory under which the shipment should be done, similar to the reorder point in inventory management (Silver *et al.*, 1998). More specifically, shipment is only made when the total amount of the on-hand inventory and in-transit inventory is inadequate to satisfy the demand during the transportation lead time. We refer this point to as the *Reshipment Point* (RSP) which can be obtained by calculating the demand during lead time at the percentile of the desired service level. The shipment policy will then be *"to assign a ship up to its full capacity to the port of destination where on-hand and in-transit inventory is less than or equal to its RSP"*. The demand at the percentile of 98% is 1,650 ton/day and 4,750 ton/day for Port B and Port C respectively. Figure 2 illustrates the daily demand distribution at Port C. We take an optimistic cycle time of about 4.5 days to ship to Port B and 5 days to ship to Port C, the RSP for Port B is 7,312 tons and for Port C is 23,750 tons. If the cycle time is constant, the above RSP would give almost 100% service level. Given that the cycle time is highly variable, the service level would be much lower. Our initial simulation experiments show that the above RSP provide about 97% - 98% service level, which is quite close to the performance of the existing system. If there is a possibility to obtain the distribution of demand during the cycle time, then a better way of setting RSP is to obtain the desired percentile from the distribution of demand during the cycle time.
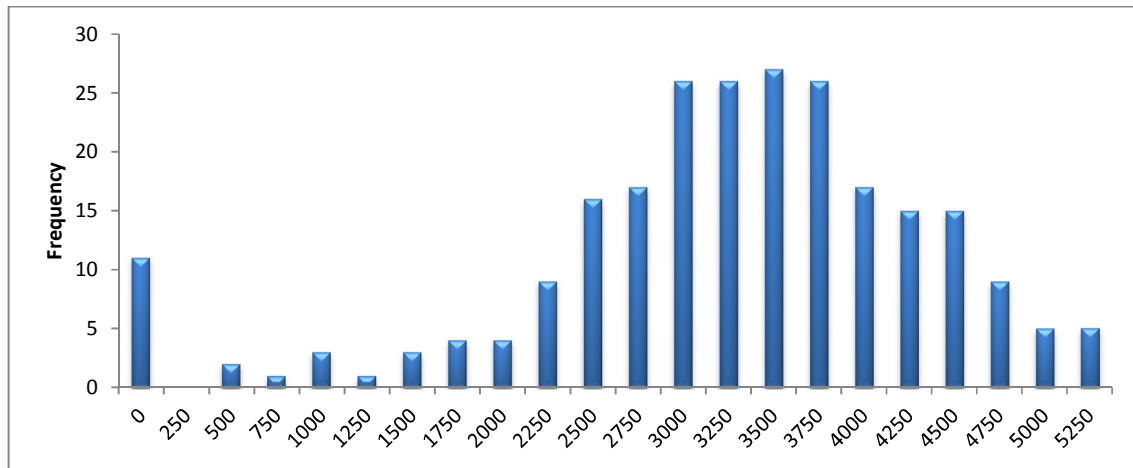
Figure 2. Daily demand distribution in the packing plant of Port C

Outline of Research Methodology

We use simulation as research methodology. We adapted the standard simulation methodology in this study (see for example Law & Kelton (2000) for the suggested steps in a simulation study). Simulation has been considered as an appropriate research method for modelling and experimenting complex system, including logistics and supply chain problems, where 'what-if' analysis is necessary (Terzi & Cavalieri, 2004). Furthermore, simulation models are often used when the characteristics of the supply chain are impractical and difficult to model with analytical approaches (Riddals *et al*., 2000) or when the systems incorporates stochastic variables and uncertainty, for instance in the case of complex inventory problems (Fleish and Tellkamp, 2005).

There are a number of major steps carried out in this study. Figure 3 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 the two response variables (cost and service level) by the use of ANOVA. The efficient frontier curve was then

constructed based on the results of all experiments. The idea of using frontier analysis is to identify few solutions that lie in the frontier line, that is, the solutions that give competitive results in terms of cost and service level. After obtaining few non-dominated solution alternatives, we did extensive experiments with 30 replications each. This enables us to construct the frequency distribution of cost and service level for each non-dominated alternative. The frequency distribution of the cost and service level is a critical information when the system works under uncertain situation. It informs us how uncertainty transforms into variations of the system performance. The details of each step will be elaborated in the following sections.
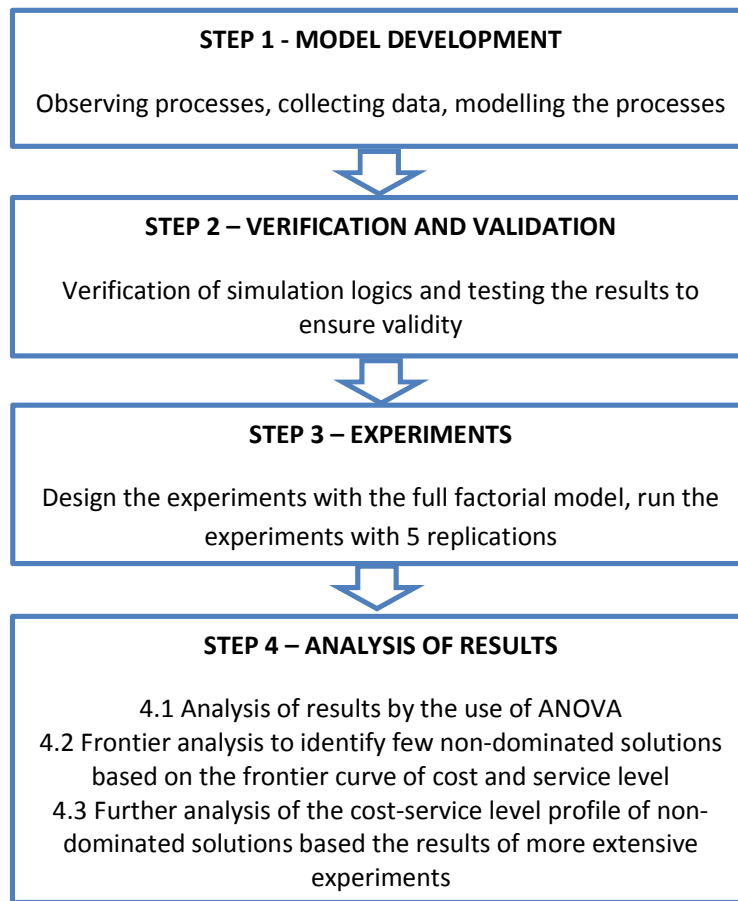

STEP 1 - MODEL DEVELOPMENT

Observing processes, collecting data, modelling the processes

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STEP 2 – VERIFICATION AND VALIDATION

Verification of simulation logics and testing the results to ensure validity

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STEP 3 – EXPERIMENTS

Design the experiments with the full factorial model, run the experiments with 5 replications

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STEP 4 – ANALYSIS OF RESULTS

4.1 Analysis of results by the use of ANOVA
4.2 Frontier analysis to identify few non-dominated solutions based on the frontier curve of cost and service level
4.3 Further analysis of the cost-service level profile of non-dominated solutions based the results of more extensive experiments

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Figure 3. Outline of major research steps

Model Development

The fundamental notion of the process model developed in this study is to attain the demand fulfillment and striking a balance between the demands at each packing plant and the

products delivered from port of origin to the packing plant located at port of destination. While the products are flowing downstream, the ships move in both downstream and upstream directions, following a closed-loop path.

Figure 4 illustrates the activities of a ship in one complete cycle. Starting from a stationary position at the port of origin, the first activity is "*wait for depot port*" to go to one of the ports of destination. Once assigned, the ship will go through the so called a *pre-time* state which includes such activities as connecting with tug boat, preparing necessary documents, etc. Once it is done, the ship may need to *wait for the depot silo* at the port of origin to be ready for loading. When the silo is ready, the loading process may start. After completing the loading process, the ship will undergo the so called *post-time in depot*. If the weather permits, then the ship may depart, otherwise the ship has to wait. Statistically, there is a seven percent chance that a ship has to wait due to weather concerns.

When a ship arrives at the port of destination, it may directly unload the bulk cement onto the silo provided if the ship arrives within the working hour of the port, there are no weather problems, the unloading dock is available, and the empty space inside the silo exceeds a certain minimum level. The last condition is important to ensure that the unloading process is completed before the silo becomes full. A simple mathematics applies for this purpose. Suppose that D is demand rate, U is unloading rate from ship to silo, SC is ship capacity, the minimum empty space inside the silo to start unloading would be $SC\,(1 - D/U)$.

Once the unloading process is completed, the ship will go back to the port of origin (Port A). The *pre-time* and *post-time* activities also apply in the port of destinations. In this model, some ships are dedicated to Port C only and some others can be assigned to any of the two ports of destination.
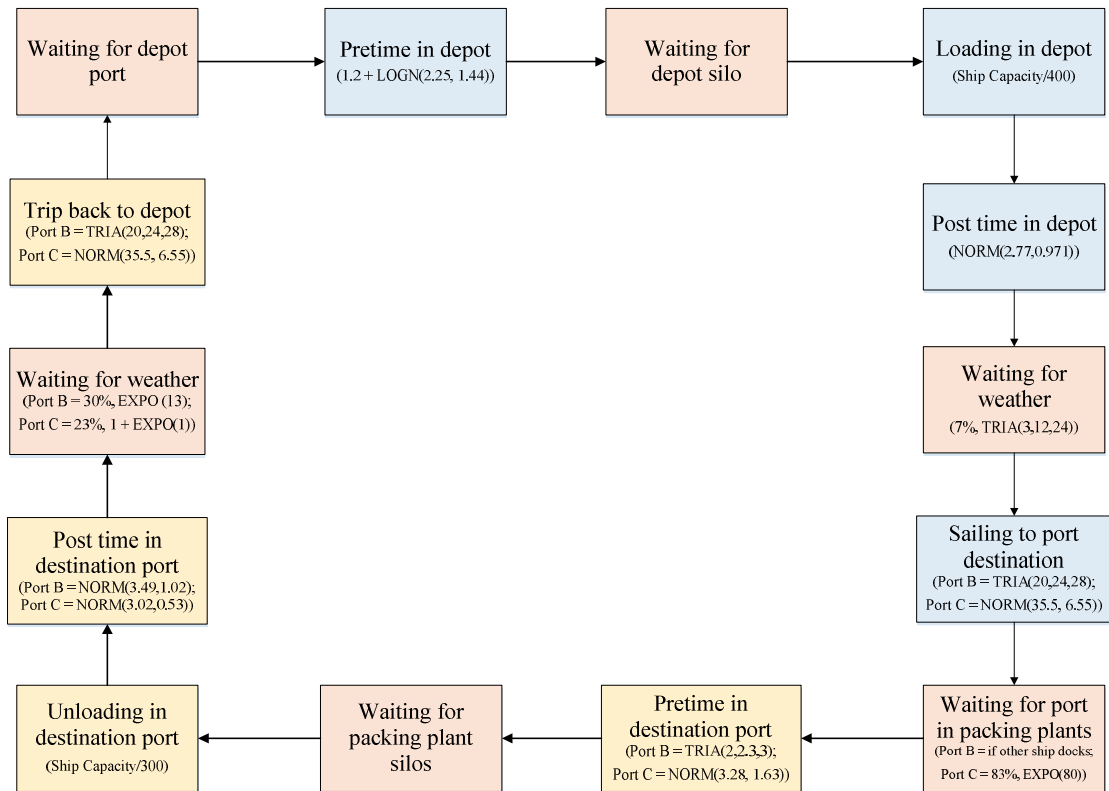
Figure 4. Ship activities and movements from port of origin to port of destination *vice versa*

The simulation flowchart is shown in Figure 4. The distribution and parameter values of each activity are obtained from the empirical data provided by the cement company. We first attempted to fit the data to the theoretical probability distributions. As shown in Figure 4, some of the processes follow the normal distribution, while others follow exponential, lognormal, and triangular distributions. In the simulation model, we generated the activity time according to those distribution. ARENA$^{\circledR}$ has been used to build the simulation model.

In general, the model can be divided into a number of sub-models, including:

- *Ship activities* which are the main model that governs the ship activities throughout the cycle.
- *Hourly-based events* which perform activities that are defined as hourly events including (i) inventory replenishment in a depot, (ii) demand fulfillment in the packing plants, (iii) ship dispatching, and (iv) clock counter updating.

- *Daily based events* that perform activities defined as daily events which include (i) generating daily demand, (ii) updating service level, (iii) reporting demand and inventory position.

- *Periodical based events* that handle the process of periodically writing simulation outputs into a spreadsheet.

These sub-models play important roles either for modeling or reporting purposes. In addition to the sub-models, a simulation dashboard has been constructed to facilitate experimentation and monitoring purposes.

The general steps in the simulation model are as follows. The more detailed process is presented in the form of a flowchart, shown in Figure 5:

Step 1. Initialization of stock on hand, stock in transit and ship in transit

Step 2. Generate demand in each market area covered by each packing plant

Step 3. Update stock position in silo of destination. Stock position = stock on hand + stock in transit. If stock position is less than RSP go to step 4, otherwise go to step 2.

Step 4. Ship available in port of origin? If yes, then assign shipment. Otherwise, hold the ship.

Step 5. Generate time of all activities to be followed by the ship. When ship is departed, update ship in transit and stock in transit. Stock in transit = stock in transit + ship capacity.

Step 6. Ship arrives at port of destination? If yes, then check the constraints. Any condition that holds ship? If yes, then wait. Otherwise, unload.

Step 7. While unloading, update inventory on-hand and inventory in-transit. Update ship status. When unload is done, return the ship to port of origin.

Step 8. Ship arrives back? If yes, then update ship status. Return to step 2.

We use the two most important performance measures of logistics, i.e. average cost per ton and service level. These two performance measures are widely recognized as two most important indicators that have been used in distribution management (Farahani & Elahipanah, 2008); in supply chain planning (Gupta & Maranas, 2003); and in supply chain design (Christopher & Towill, 2001). Average costs consist of investment costs of constructing

additional silos and shipping costs, calculated for a certain period of time, given by the following expressions:

$$Cost\ per\ ton\ = \frac{investment\ cost\ (IC)\ +\ shipment\ cost\ (SC)}{total\ amout\ of\ shipments\ (AS)}$$

where

$$IC = number\ of\ additional\ silos\ \times Investment\ cost\ per\ silo\ x\ AF$$

Where AF is the constant used to convert the present value of the investment cost to its annual equivalent under a certain assumption of economic life and interest rate. In this study we have assumed that the economic life of a silo is 20 years and the annual interest rate is 12%. In this study, we ignore the additional inventory holding cost as a result of the increase in silo capacity due to its trivial contribution to the logistics costs. Our rough calculation suggests that the increase in inventory holding cost due to adding silo capacity is less than 0.1% of product cost. The inventory holding cost should already include cost of capital of inventory tied up in the storage, physical depreciation, storage and handling, obsolescence, taxes, and insurance (Ballou, 1999). In other situation where the portion of inventory holding cost is substantial, it should be included in the calculation of total cost.

Shipment costs consist of two different rates applicable for both off-road (non-moving) and on-road (moving) times of the vessels. During the on-road time, the chartering rate includes the fuel cost (full chartering rate). When off-road, the chartering rate only includes payment for ship owner (off-road chartering rate). The mathematical expression of the shipping costs is as follows:

$$SC = ORC\ \times ORT\ + FCR\ \times\ FCT$$

where ORC is the off-road chartering rate, ORT is duration of the off-road time, FCR is full chartering rate, and FCT is the duration of on-road time. The average cost per ton is thus the total cost given by the above expression divided by the total volume shipped during the corresponding period.

Service level is the measure of stock availability at each destination. Given that we have two ports of destination with different demand rates, we aggregate service level of the two locations as follows:

$$SL = \left(\frac{DB}{TD}\right) \times SLB + \left(\frac{DC}{TD}\right) \times SLC$$

where DB is the demand at Port B, DC is the demand at Port C, TD is the total demand, SLB is the service level at Port B, and SLC is the service level at Port C. The service level itself can be obtained by dividing the number of days at a particular port without stock-out by the total number of days in one year, expressed as follows:

$$SLB = \frac{number\ of\ days\ without\ stockout\ in\ B}{number\ of\ days\ in\ one\ year}$$

Verification and Validation

Verification and validation are the two critical steps in a simulation study (Kleijnen, 1995; Sargent, 2013). Verification ensures that the logic of the simulation model works as intended, while validation ensures that the model represents the real system. In this simulation study, model verification and validation were performed before running the experiments. Verification was performed by examining several simulation processes separately to check whether the model behaves according to its design or all variables were updated to their new values correctly. More specifically, we examined a number of procedures including: (i) the procedure for ship assignment (checking that ship is assigned if the stock position is below the RSP); (ii) the calculation of service level (assuring that our manual calculation produced the same results as that of the software); (iii) cycle time calculation (ensuring that it has been computed correctly by the software). Validation was carried out by statistically comparing the cycle times and cost per ton of the output of scenario 0 (that represents the initial condition) and the corresponding data obtained from the company. Both verification and validation demonstrate that the simulation model was appropriately developed and reasonably credible.
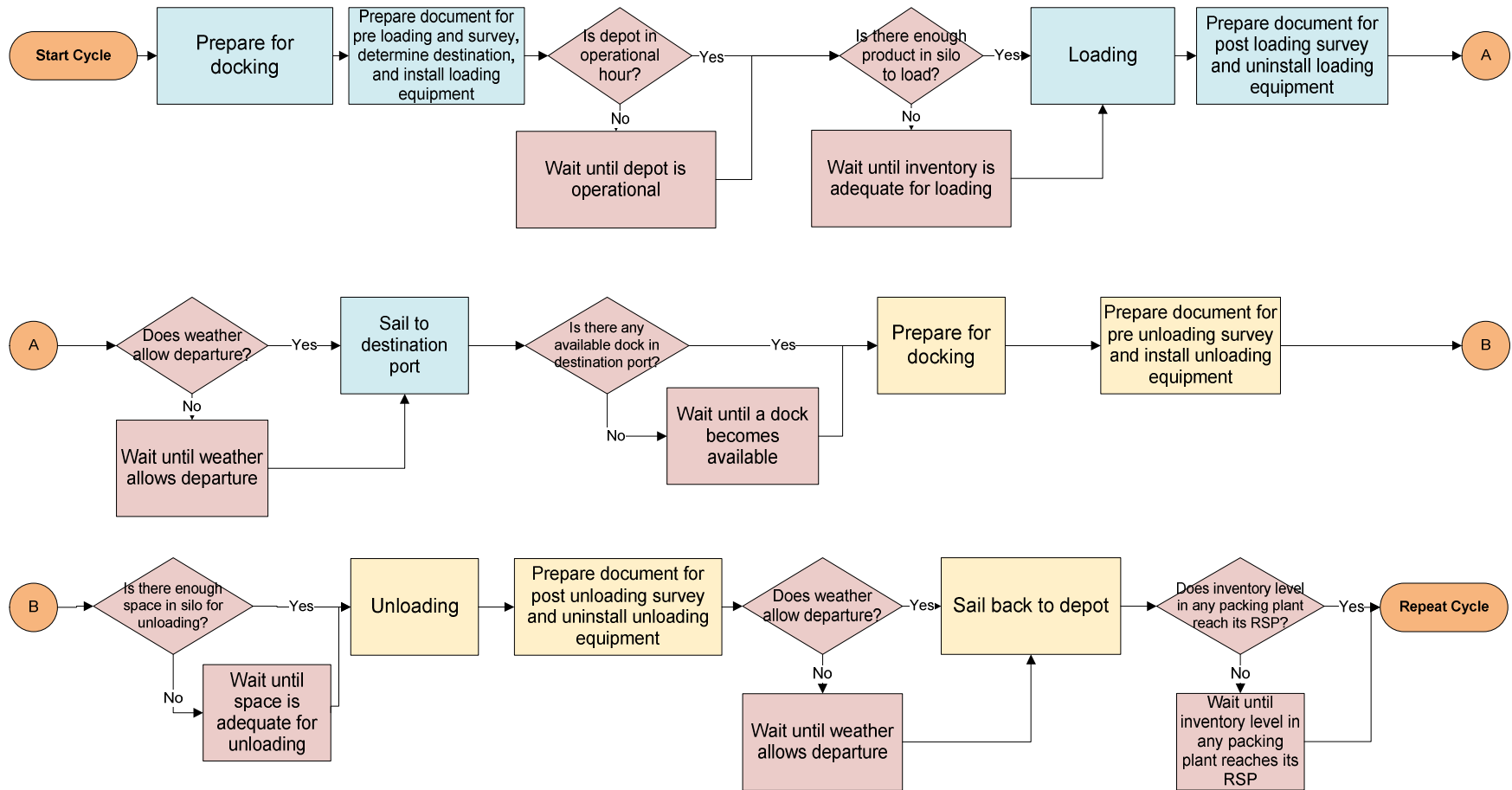
Figure 5. Flowchart of the simulation model

Experiments

In this study we attempted to find alternative ways to reduce the logistics costs while maintaining an acceptable service level. We believed that there is an interrelationship between the capacity of silo at the port of origin, the number (and hence the total capacity) of ships, and the capacity of silo at the port of destination. We may treat those three stages as interconnected activities that should have balanced capacity in order to improve the throughput, i.e. to fulfill the demand at the lowest possible cost. However, given the complexity of the problem, how those factors interact one another are not obvious and therefore simulation experiments would be required.

We use a full factorial experimental design in this study. This type of factorial design is most efficient in a study of the effects of two or more factors (Montgomery, 1997). In the context of experimental design, factors refer to input parameters and structural assumptions while responses refer to the output performance measures (Law & Kelton, 2000). In this study we investigate four factors where each corresponds to possible changes in the operations of the logistics systems, namely:

1. *Reducing the number of ships*, which will directly reduce the transportation costs, but it may also reduce the service level. Therefore, we wanted to determine the minimum number of ships we employ to meet such an acceptable service level. As shown in Table 1, we include 3 levels of "number of ships", namely 6, 5, and 4.

2. *Increasing the storage capacity at the port of origin and at one of the ports of destination* (in this case the silo at Port C because of its high demand and large proportion of ship waiting). This will obviously increase the storage costs and for this purpose, we have estimated the annual cost for silo investment and then distributed this cost across the total logistics cost. The two alternatives of silo capacity are: (i) 11,000 tons, which is the current capacity level and (ii) twice the current capacity, which means that the company has to build an additional silo at the same capacity as the existing one.

3. *The use of RSP*, that is, dispatching ship only if the inventory position, that is, the on-hand inventory in the silo plus the in-transit inventory falls below the reshipment points (RSP). This is in contrast to the current practice where any available ship is loaded and dispatched (i.e. the RSPs have unlimited values). The use of RSP is expected to improve the overall performance of the system as any ship waiting at the

port of origin offers better flexibility compared to a ship waiting at the port of destination.

4. *Ports are operating longer each day*. Currently some ports are operating only 12 hours a day. We would like to test the impacts of extending the working hour at each port to 24 hours a day non-stop. This is expected to reduce waiting time of ships in all ports and therefore would have a substantial impact on the distribution cost per ton of product.

We designed a full factorial simulation experiment. As shown in Table 1, there are five factors included in the experiments, each with two or three levels, giving a total of 48 experimental cells or treatments. The number of replications in each experimental cell is five, leading to 240 individual experiments. ARENA® process analyzer was used to help setting the parameters in each treatment. In addition, we also run experiments for further four selected treatments to obtain insights on how each of these leads to different performances (costs and service level).

Table 1 is about here

Analysis of Results

ANOVA for Significance Tests

The simulation results in terms of cost per ton and service level have been analyzed. Table 2 shows the percentage difference in average cost per ton for each experimental treatment compared to the base model that represents the current state. In Table 3 we present the same format for the service level. Note that the current state is represented by NS = 6, OT = 12, RS = 1, DE = 1, and PC=1. For the base model, the absolute value of cost per ton is 220 thousands of rupiahs and the service level is 97%. ANOVA (Analysis of variance) test has been conducted to evaluate the impacts each factor gives on each of the two performance measures. The principle of ANOVA test is to statistically compare the effect of different treatments bring on the performance measure (Montgomery, 1997). When the means are statistically different, then varying the treatment of the corresponding factor significantly affects the performance. The use of ANOVA to identify the factors that significantly affect the performance of a system has been widely used in manufacturing and supply chain

research, including for example Ho (2002), Frohlich & Westbrook (2001) and Yeung *et al.* (2006).

Tables 4 and 5 present the results of the ANOVA test for the main effect and the two-way interactions. All factors have significant impact on both total costs and service level which is shown by the small values (less than 5%) of significance level. Most interactions are also significant. For example, for both cost and service level, all interactions involving the number of ships (NS) are shown to be significant. This means that the effect of number of ships on the total costs and service level is affected by all other factors.

Tables 2 and 3 are bout here

One of the most obvious findings is that reducing the number of ships decreases both average cost per ton as well as the service level. This is because we applied the time-charter assumption for all ships. The cost reduction could be as high as 20% to 23% if the number of ships is reduced from six to four and the working time of ports is increased to 24 hours. Reducing the number of ships to five gave about 11% to 14% difference in terms of total costs. On the other hand, reducing the number of ships would reduce service level up to about 7%, but such a decrease could be moderated or even prevented if storage capacities are extended (see Table 3). In the ANOVA tables (Tables 4 and 5), the significance of effect of the number of ships operating is zero for both service level and costs, confirming that the number of ships is significantly affecting both service level and costs.

Table 4 is about here

From Table 3 it can also be seen that the use of four ships will not deliver the acceptable service level if the ports are working for 12 hours. However, with the 24 hours operating time and by extending the storage capacity to 22,000 tons, it would be possible to achieve almost the same service level as the current state, which is about 97%. When the number of ships is decreased to five, some treatments show reduction in service level which

is represented by negative values but there are many other treatments that could deliver better service level. Improvement in service level is particularly achievable when the storage capacities (both at Port A and Port C) are extended to 22,000 tons. This means that it is possible to reduce costs and improve service level at the same time even if the number of ships is reduced. Nonetheless, this should be coupled with higher storage capacities along the distribution network. This finding is in line with our initial conjecture.

Overall, the impact of extending the working hour from 12 to 24 is significant in terms of costs and service level although the results also suggest that its impact on cost is more apparent than that on service level. When four or five ships were employed, the total average showed about 3% reduction in cost due to the extension in working hour, but such a reduction is only about 1.3% when there were six ships used. This implies that working time extension is more important when the number of ships is lower. The ANOVA table also confirms the interaction effect between operating time and number of ships on cost as well as on service level.

Table 5 is about here

The reshipment point (RSP) has a significant effect on both cost and service level. This is in fact an interesting discovery. The idea of setting up an RSP value is to avoid a ship waiting too long at the port of destination due to insufficient empty space in the silo at the time the ship arrives. A ship is departed to a destination only if the inventory position at the port of destination is equal or below the RSP value. This supports our premise that it is better to hold ships at the port of origin until the stock at the port of destination reaches the reshipment point rather than dispatching the ships whenever they are available. Unlike adding the silo capacity which is an expensive investment, the use of RSP is essentially a modification of the dispatching rule which does not cost the company anything.

Efficient Frontier Analysis

The trade-off between cost and service level is well known in logistics, however, such a relationship is obvious when we varied the level of inventory under uncertain supply and

demand, i.e., higher inventory normally results in higher service level. A clear cost and service level trade-off also exists in location problems, i.e., establishing more facilities add costs but bring products closer to customers (Shen & Daskin, 2005). In the maritime logistics context, there exists some trade-offs between cost and service level. For example, Fagerholt (2010) evaluated the trade-off between customer service and cost in a ship scheduling problem.

In this study we suspected that there is also a strong trade-off between costs and service level. The reason is that, when we invested in a higher storage capacity, there should be a higher stock availability, but there is also a cost associated with this investment. On the other hand, the decision to reduce the number of ships would reduce costs but result in a lower stock availability. Given that there are many interrelated factors, the trade-off is not obvious and some complex interactions emerge, for example, port operating hours that also affect the service level. There is a case of higher service level attained by extending operations time to 24 hours even if the silo capacity is lower.

Efficient frontier analysis is a popular technique to find non-dominated alternatives in a multi-criteria decision making. In the context of logistics and supply chain problems the efficient frontier analysis has been used, for example, in logistics network design that consider both environmental and business objectives (Frota Neto *et al*, 2008). In Figure 6, we plot the cost per ton (vertical) against the service level (horizontal) for each experiment. Note that each color in Figure 6 represents a treatment. The general pattern shows that there is a correlation between cost and service level, i.e., higher service level is achieved with higher costs. From this figure we can also identify the approximate frontier line that connects the most competitive options (which is shown by the dotted curve at the bottom part of the graph). The points which are far from the frontier curve are dominated options. The frontier curve can be used to guide the cost and service level targets for the company.

It is interesting to see which combination of levels that leads to the efficient frontiers and which ones that are mostly dominated. It is important to note, however, that there should be a lower limit of acceptable service level. The e current state is shown in scenario 0 where inside the circle there are five observations, each from a single replication. It is obvious that scenario 0 is dominated by many other scenarios. In this instance, we are particularly interested in three other scenarios (3, 23, and 39) which lie around the frontier line and the results among different replications do not exhibit much variability. There are also some

other experiments that are quite close to the frontier line but they exhibit quite large variability among replications. For example, some replications of scenario 19 look quite competitive but other replications are not. In the following sub-section we will explore further the distribution of service level and costs for the four chosen scenarios.

Frequency Distribution of Cost and Service Level of Non-Dominated Alternatives

As transport is a vital part of a supply chain, uncertainty in transport operations would ultimately affects the ability of a supply chain to respond to the demands (Rodrigues *et al*., 2010). The more uncertain the situation is, the more difficult it would be for a company to achieve consistent performance or to achieve the desired objectives (van der Vorst & Beulens, 2002). In this study we modeled a situation characterized by high uncertainty. First, the demand at each silo is stochastic. Second, the ship movement is encountering uncertainties in almost any stage of the process cycle. For example, at the time a ship arrives at the port of destination, there maybe a weather problem that prevents it to dock and unload the bulk cement. In the case of weather problems, the waiting time could be substantially longer which then affects the cycle time, cost and service level.

Under uncertain situation, it would be useful to understand the variation in the system performance. Therefore, it is insufficient to only observe the average value of the cost and service level as shown in Tables 2 and 3, but the differences in the cost and service level from one replication to the other should be observed. Ideally cost and service level profile is represented in the form of a frequency distribution. For this purpose, we run 30 replications of the four scenarios, one is representing the current state (scenario 0), and the other three are representing the competing points at the efficient frontier mentioned above, namely scenarios 3, 23, and 39. To improve clarity, Table 6 shows the definition of those 4 scenarios. Note that scenarios 3, 23, and 39 represent six, five, and four ships operating respectively.

Table 6 is about here

Figure 7 shows the distribution of cost per ton of the four scenarios. The results of the 30 replications for each scenario indicate that the three alternative scenarios (3, 23, and 39)

result in significantly lower cost per ton compared to the scenario 0. It is interesting to note that even though extending the silo capacity is costly, doing so will help the ships to move faster along the transportation cycle and thus results in lower overall costs. The distribution of service level is exhibited in Figure 8. Unlike the distribution of cost showing clear differences among the four scenarios, Figure 8 suggests that the profile of service level among those four scenarios is not showing significant differences, but a careful evaluation suggests that scenarios 3 and 23 gave better service level than scenarios 0 and 39. In deciding which of these would be the choice, managers need to think about the trade-off between cost savings and service level decrease. Would it be worthwhile to sacrifice about 10% in cost to achieve 1% higher in service level? If not, then the choice would be to opt for a lower service level to warrant the cost savings. In most of the cases, managers with modest risk aversion would likely avoid scenario 39. The choice could also be affected by the market structure. In a monopoly situation, typically there is not so much concern on a somewhat low service level, but certainly this is not the case in a highly competitive market. As suggested by Christopher & Towill (2001), each company may opt for a different strategy, i.e., whether cost or service level that become the market winning factor. Reflecting the case of the cement company in this study, cost is indeed a major concern, but achieving between 97% and 98% service level would be acceptable, indicating the preference toward scenario 3 or 23.
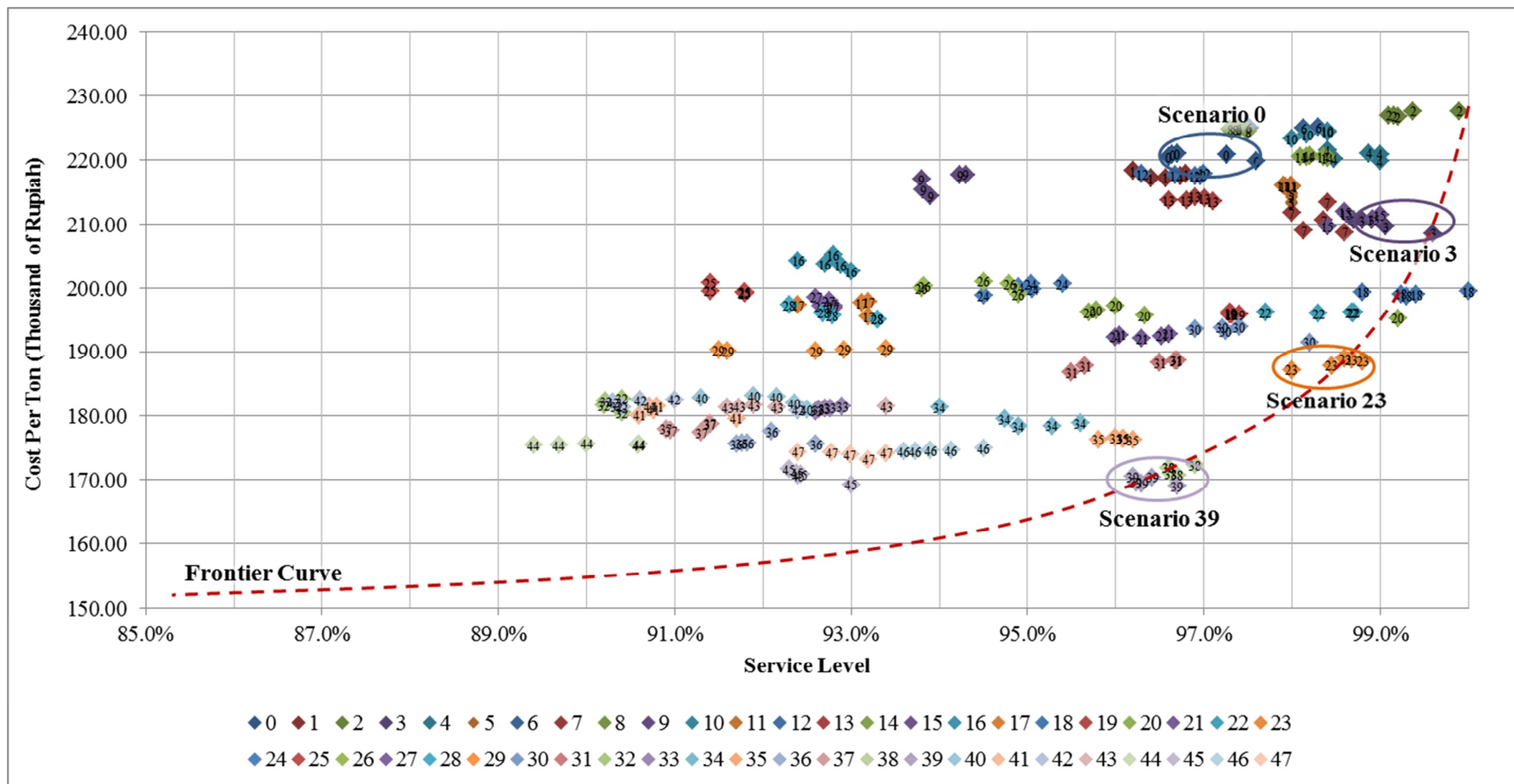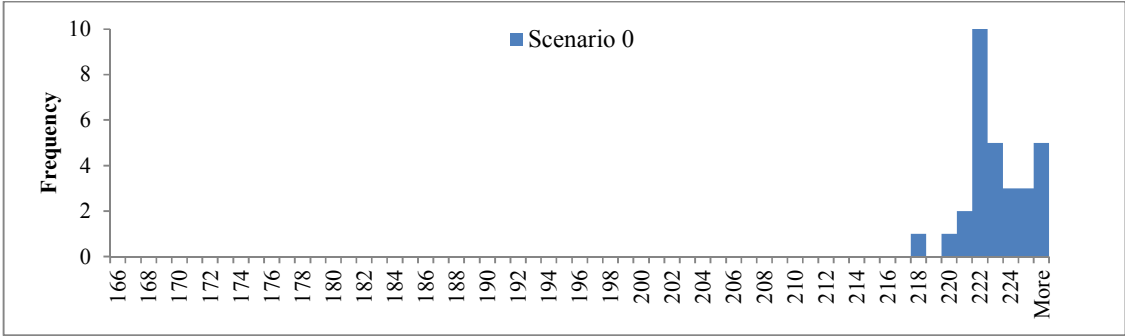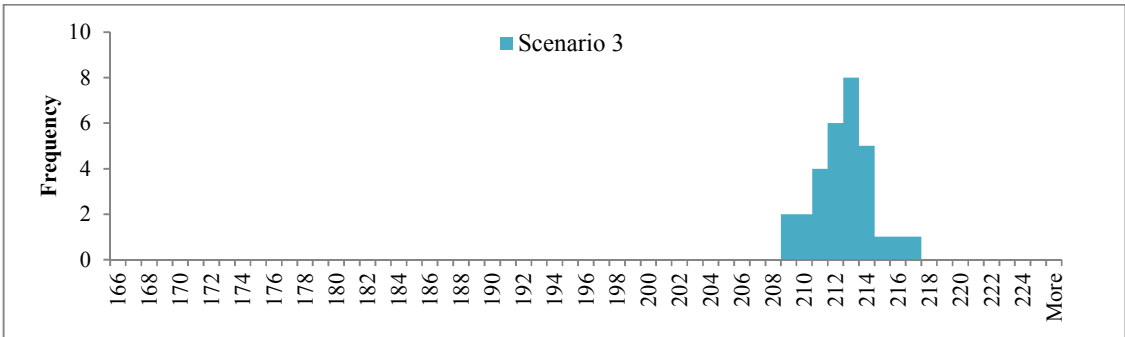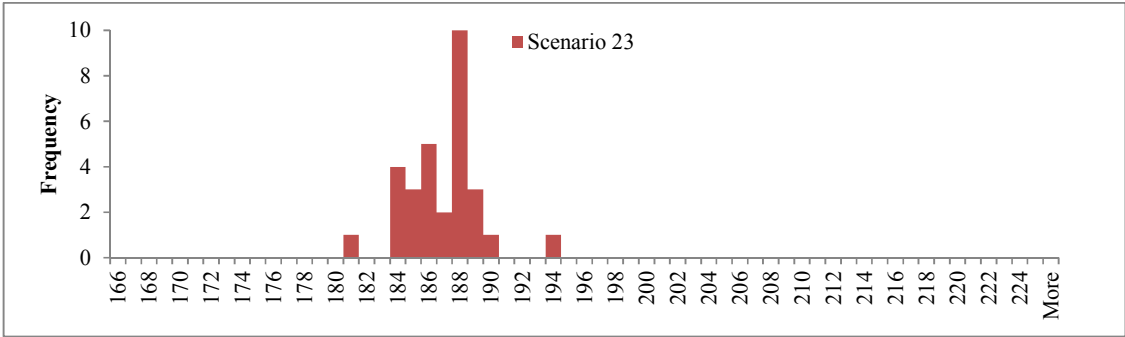
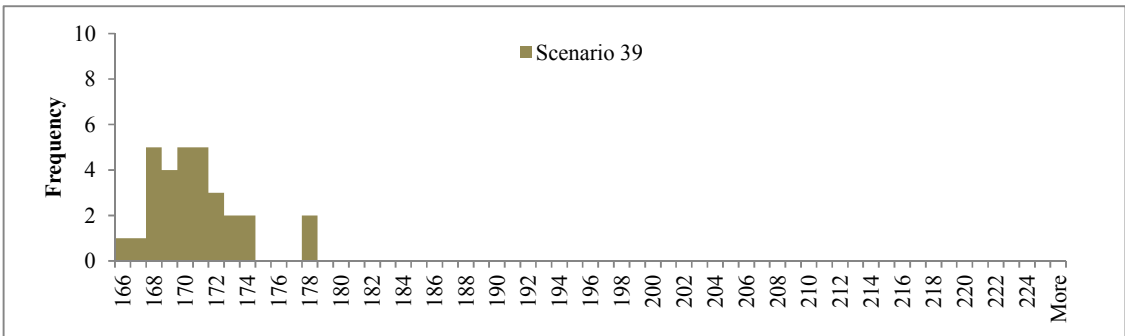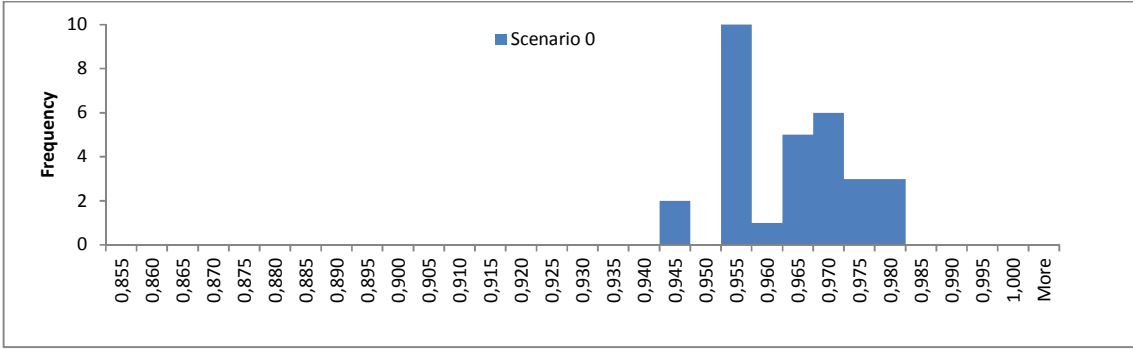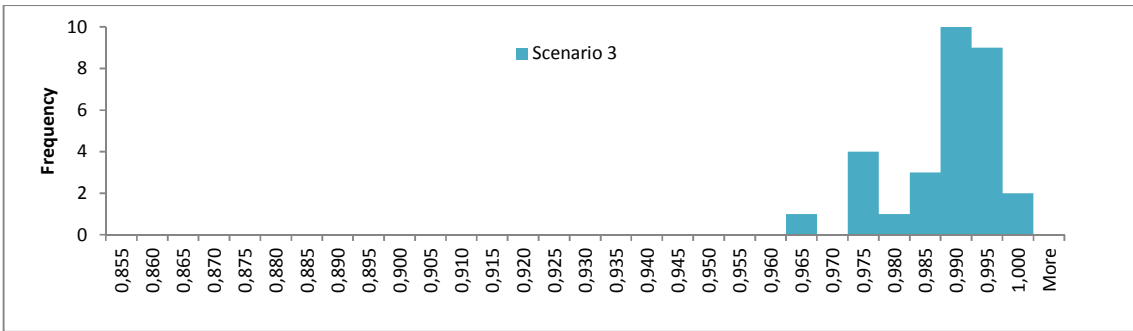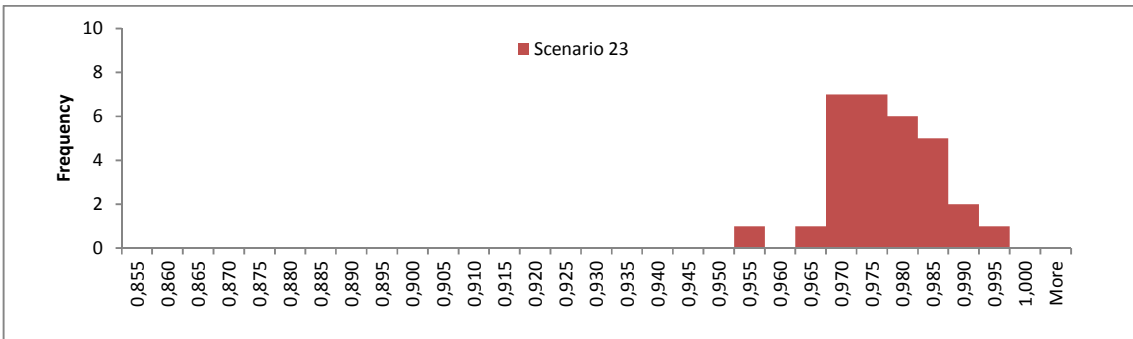**Figure 6.** Cost-service level efficient frontier

(a)

(b)

(c)

Figure 7. Distribution of cost per ton of the four scenarios
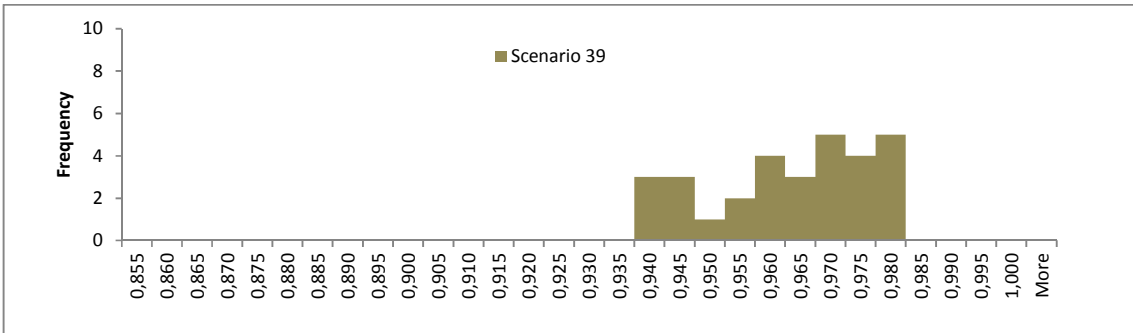
(a)

(b)

(c)

(d)

Figure 8. Distribution of service level for the four scenarios

Discussion and Conclusion

This paper presents a simulation study of bulk cement distribution in Indonesia via the maritime transport from one port of origin to two ports of destination. We investigated five factors that we suspected to have impact on total costs and service level. We demonstrated that all factors have significant effect on total costs as well as service level. Further observation showed that some interactions between factors also have significant impact on both performance measures. We plotted the trade-off between service level and costs. It is obvious that there is a correlation between cost and service level but some scenarios are obviously dominating others. The use of the efficient frontier of cost-service level has enabled us to obtain the candidates for our best scenario. Under uncertain environment, obtaining a consistent supply chain performance is important (van der Vorst & Beulens, 2002). The presence of uncertainty forces decision makers to work with buffers (van der Vorst & Beulens, 2002).In a maritime transport, variability in transit time in a port requires higher safety stock at the receiving side (Harrison & Fichtinger, 2013). Hence, in order to provide a robust recommendation, the competing scenarios should be extensively compared based on various detailed performances, not only using their average values, but also variability of each performance indicator. In this study we have been able to show variability in logistics performance (i.e., cost and service level) of four selected scenarios by the use of frequency distribution.

When the charter time is applied for all ships, a sensible way of reducing the logistics cost is to reduce the number of ships. This idea was driven by the fact that the current level of congestion in ports is very high. This congestion problem is recognized widely in earlier studies related to maritime transport (for example Harrison & Fichtinger, 2013). However, reducing number of ships may have an impact on the service level. The simulation results suggest that the number of ships deployed, silo capacity, working hours of ports, and the dispatching rules of ships significantly affect both total costs and service level. Interestingly, operating fewer ships enables the company to achieve almost the same service level and gaining substantial cost savings if constraints in other part of the system are alleviated, i.e., storage capacities and working hours of ports are extended. This implies that any attempts to reduce costs should go beyond the shipment planning, toward a more holistic view to alleviate constraints in other parts of the system. However, it is important to note that such initiatives would require attention of a different management hierarchy in the organization. While shipment planning is tactical and operational in nature, adding storage capacity is often

a major investment that requires top management's approval. Adding silos, even though a costly investment, however, could reduce the total costs due to faster ship turnaround from point to point. In a complex system connecting silos and ships with uncertain demand and travelling conditions, it is necessary to analyze the interplay between various factors (and decisions) in order to provide the best possible improvement idea.

This paper offers a new way of combining both strategic and operational decision parameters in the form of a simulation-based decision making tool. We demonstrated that, by using simulation modelling, the impracticality and difficulty of analytical methods especially when the system exhibit uncertainties and incorporates stochastic variables can be overcome. Simulation is a powerful tool that can help decision makers in evaluating different design alternatives that could lead to the determination of the most effective course of actions in a complex and uncertain environment like the one that we modeled in this study. The combination of simulation and the efficient frontier analysis (to screen the non-dominated solutions) provided us with best solutions with minimal experimentation times to trade-off logistics costs and service level (availability).

For future work, we intend to extend our study to include an investigation of the supply chain flexibility. Angkiriwang *et al*. (2014) suggested various strategies of flexibility that could be applied to deal with uncertainties. In this study, we tested a number of scenarios related to creating better supply chain flexibility. For example, the use of RSP has an implication on the system flexibility because ships that are available at the port of origin may be held up until the stock level at the port of destination reaches a certain level. Increasing the storage capacity is also a strategy that could improve supply chain flexibility. Another possible scenario is to increase the loading and unloading speed which could also potentially improve logistics performance. The impacts would not be obvious as speeding up unloading from vessel to silo has no point if the silo if full or almost full. In addition there is cost associated with acquisition of faster loading and unloading equipment and thus, such a complex interaction requires a simulation model to evaluate these alternatives.

Recently there is a growing concern on how to handle uncertainty in the design and operations of a supply chain (Pujawan *et al*., 2014). As suggested by Rodrigues *et al*., (2008; 2010), there is a growing interest on how to manage uncertainty not only from manufacturing perspective, but also from transportation point of view. Clearly our paper is contributing to the knowledge enrichment of uncertainty in transport operations and physical distributions.

Acknowledgements

References

Al-Khayyal, F., & Hwang, S.-J. (2007), "Inventory constrained maritime routing and scheduling for multi-commodity liquid bulk, Part I: Applications and model", *European Journal of Operational Research,* Vol. 176, No.1, pp. 106-130.

Angkiriwang, R., Pujawan, I N., and Santosa, B. (2014), "Managing uncertainty through supply chain flexibility: reactive vs. proactive approaches", *Production & Manufacturing Research: An Open Access Journal*, Vol. 2, No. 1, pp. 50 - 70.

Ballou, R. H. (1999), *Business Logistics Management: Planning, Organizing, and Controlling the Supply Chain*, Fouth Ed., Prentice-Hall.

Christiansen, M. (1999), "Decomposition of a combined inventory and time constrained ship routing problem", *Transportation Science,* Vol. 33, No. 1, pp. 3-16.

Christiansen, M., Fagerholt, K., Flatberg, T., Haugen, Ø., Kloster, O., & Lund, E. H. (2011), "Maritime inventory routing with multiple products: A case study from the cement industry", *European Journal of Operational Research,* Vol. 208, No. 1, pp. 86-94.

Christiansen, M., Fagerholt, K., Nygreen, B., & Ronen, D. (2006), "Maritime transportation", *Transportation,* Vol. 14, pp. 189-284.

Christiansen, M., Fagerholt, K., Nygreen, B., & Ronen, D. (2013), "Ship routing and scheduling in the new millennium", *European Journal of Operational Research,* Vol. 228, No. 3, pp. 467-483.

Christopher, M., & Towill, D. (2001), "An integrated model for the design of agile supply chains", *International Journal of Physical Distribution & Logistics Management*, Vol. 31, No. 4, pp. 235-246.

Coelho, L. C., Cordeau, J. F., & Laporte, G. (2012), "The inventory-routing problem with transshipment", *Computers & Operations Research*, Vol. 39, No. 11, pp. 2537-2548.

De Souza, R., Goh, M., Gupta, S., & Lei, L. (2007), "An investigation into the Measures Affecting the Integration of ASEAN's Priority Sectors, Phase 2: the Case of Logistics", *REPSF Project*, 6.

Dauzère-Pérès, S., Nordli, A., Olstad, A., Haugen, K., Koester, U., Per Olav, M. (2007), "Omya Hustadmarmor optimizes its supply chain for delivering calcium carbonate slurry to European paper manufacturers", *Interfaces,* Vol. 37, No. 1, pp. 39-51.

Fagerholt, K. (2000), "Evaluating the trade-off between the level of customer service and transportation costs in a ship scheduling problem", *Maritime Policy & Management*, Vol. 27, No. 2, pp. 145-153.

Farahani, R. Z., & Elahipanah, M. (2008), "A genetic algorithm to optimize the total cost and service level for just-in-time distribution in a supply chain", *International Journal of Production Economics*, Vol. 111, No. 2, pp. 229-243.

Fleisch, E., & Tellkamp, C. (2005), "Inventory accuracy and supply chain performance: a simulation study of a retail supply chain", *International Journal of Production Economics*, Vol. 95, pp. 373-385

Frohlich, M. T., & Westbrook, R. (2001), "Arcs of integration: an international study of supply chain strategies", *Journal of Operations Management*, Vol. 19, No. 2, pp. 185-200.

Frota Neto, J. Q., Bloemhof-Ruwaard, J. M., Van Nunen, J. A. E. E., & Van Heck, E. (2008), "Designing and evaluating sustainable logistics networks", *International Journal of Production Economics*, Vol. 111, No. 2, pp. 195-208.

Grønhaug, R., Christiansen, M., Desaulniers, G., & Desrosiers, J. (2010), "A branch-and-price method for a liquefied natural gas inventory routing problem", *Transportation Science,* Vol. 44, No. 3, pp. 400-415.

Gupta, A., & Maranas, C. D. (2003), "Managing demand uncertainty in supply chain planning", *Computers & Chemical Engineering*, Vol. 27, No. 8, pp. 1219-1227.

Halvorsen-Weare, E. E., & Fagerholt, K. (2013), "Routing and scheduling in a liquefied natural gas shipping problem with inventory and berth constraints", *Annals of Operations Research,* Vol. 203, No. 1, pp. 167-186.

Harrison, A., & Fichtinger, J. (2013), "Managing variability in ocean shipping", *The International Journal of Logistics Management*, Vol. 24, No. 1, pp. 7-21.

Ho, C. J. (2002), "Evaluating dampening effects of alternative lot-sizing rules to reduce MRP system nervousness', *International Journal of Production Research*, Vol. 40, No. 11, pp. 2633-2652.

Kleijnen, J. P. (1995), "Verification and validation of simulation models", *European Journal of Operational Research*, Vol. 82, No. 1, pp. 145-162.

Law, A. M., & Kelton, W. (2000). *Simulation Modeling and Analysis*. 3rd Ed., Mac Graw Hill, Boston.

Manzini, R., & Bindi, F. (2009), "Strategic design and operational management optimization of a multi stage physical distribution system", *Transportation Research Part E: Logistics and Transportation Review*, Vol. 45, No. 6, pp. 915-936.

Montgomery, D. C. (1997), *Design and Analysis of Experiments*, 4th Ed, John Wiley & Sons.

Natarajarathinam, M., Stacey, J., & Sox, C. (2012), "Near-optimal heuristics and managerial insights for the storage constrained, inbound inventory routing problem", *International Journal of Physical Distribution & Logistics Management*, Vol. 42, No. 2, pp. 152-173.

Panayides, P. M. (2006), "Maritime logistics and global supply chains: towards a research agenda", *Maritime Economics & Logistics,* Vol. 8, No. 1, pp. 3-18.

Pantuso, G., Fagerholt, K., & Hvattum, L. M. (2014), "A survey on maritime fleet size and mix problems", *European Journal of Operational Research*, Vol. 235, No. 2, pp. 341-349.

Persson, J. A., & Göthe-Lundgren, M. (2005), "Shipment planning at oil refineries using column generation and valid inequalities", *European Journal of Operational Research*, Vol. 163, No. 3, pp. 631-652.

Pujawan, I. N., Er, M., Kritchanchai, D., & Somboonwiwat, T. (2014), "Uncertainty and schedule instability in supply chain: insights from case studies", *International Journal of Services and Operations Management*, Vol. 19, No. 4, pp. 468-490.

Riddalls, C.E., Bennett, S., Tipi, N.S. (2000), "Modelling the dynamics of supply chain", *International Journal of Systems Science*, Vol. 31, pp. 969-976.

Rodrigues, V. S., Stantchev, D., Potter, A., Naim, M., & Whiteing, A. (2008), "Establishing a transport operation focused uncertainty model for the supply chain", *International Journal of Physical Distribution & Logistics Management*, Vol. 38, No. 5, pp. 388-411.

Rodrigues, V. S., Potter, A., & Naim, M. M. (2010), "The impact of logistics uncertainty on sustainable transport operations", *International Journal of Physical Distribution & Logistics Management*, Vol. 40, No. 1/2, pp. 61-83.

Ronen, D. (2002), "Marine inventory routing: Shipments planning", *Journal of the Operational Research Society*, Vol. 53, pp. 108-114.

Russ, B. F., Yamada, T., Castro, J., & Yasukawa, H. (2005), "Optimising the design of multimodal freight transport network in Indonesia", *Journal of the Eastern Asia Society for Transportation Studies,* Vol. 6, No. 1, pp. 2894-2907.

Sargent, R. G. (2013), "Verification and validation of simulation models", *Journal of Simulation*, Vol. 7, No. 1, pp. 12-24.

Shen, Z. J. M., & Daskin, M. S. (2005), "Trade-offs between customer service and cost in integrated supply chain design", *Manufacturing & Service Operations Management*, Vol. 7, No. 3, pp. 188-207.

Silver, E. A., Pyke, D. F., & Peterson, R. (1998). *Inventory Management and Production Planning and Scheduling*, 3rd Ed., New York: Wiley.

Siswanto, N., Essam, D., & Sarker, R. (2011), "Solving the ship inventory routing and scheduling problem with undedicated compartments", *Computers & Industrial Engineering*, Vol. 61, No. 2, pp. 289-299.

Song, J. H., & Furman, K. C. (2013), "A maritime inventory routing problem: Practical approach", *Computers & Operations Research*, Vol. 40, No. 3, pp. 657-665.

Stacey, J., Natarajarathinam, M., & Sox, C. (2007), "The storage constrained, inbound inventory routing problem", *International Journal of Physical Distribution & Logistics Management*, Vol. 37, No. 6, pp. 484-500.

Teixeira, E.L., Tjahjono, B. and Absi Alfaro, S.C. (2012), "A novel framework to link Prognostics and Health Management and Product-Service Systems using online simulation", *Computers in Industry*, Vol. 63, No. 7, pp. 669-679.

Terzi, S., & Cavalieri, S. (2004), "Simulation in the supply chain context: a survey", *Computers in Industry*, Vol. 53, No. 1, pp. 3-16.

Van der Vorst, J. G., & Beulens, A. J. (2002), "Identifying sources of uncertainty to generate supply chain redesign strategies", *International Journal of Physical Distribution & Logistics Management*, Vol. 32, No. 6, pp. 409-430.

Yeung, J. H. Y., Selen, W., Sum, C. C., & Huo, B. (2006), "Linking financial performance to strategic orientation and operational priorities: an empirical study of third-party logistics providers", *International Journal of Physical Distribution & Logistics Management*, Vol. 36, No. 3, pp. 210-230.