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# New Approach for Evaluating Berth Allocation Procedures Using Discrete Event Simulation to Reduce Total Port Handling Costs

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## ABSTRACT

**The berth allocation problem (BAP) is a significant problem in operational or tactical planning in maritime logistics. The BAP total cost of port handling consists of demurrage/despatch and operational costs from loading and unloading facilities. The BAP becomes more complex because of the uncertainties of ship arrival, unloading time, and the interdependence between loading and unloading processes, which may cause an unpredictable completion time. This study aims to evaluate berth allocation procedures to reduce the total port handling costs. The discrete event simulation (DES) approach is used to determine the best BAP procedure and to obtain the optimal number of facilities in the BAP. Twenty scenarios are generated by combining various dock and ship selection rules. In operational planning, the chosen scenario can save the company 0.125 financial units annually regarding total port handling cost. Meanwhile, optimization tools are employed in tactical planning to reveal the ideal number of unloading facilities used. The best scenario of tactical planning can reduce total handling cost by 15% or 3.209 financial units by adding more resources in unloading facilities, such as cranes and trucks, and implementing certain mechanisms in selecting ships and docks. Lastly, sensitivity analysis is performed to test the robustness of the simulation model by modifying several influential parameters, such as (i) material type, (ii) ship arrival rate, (iii) operational cost rate, (iv) demurrage rate, and (v) target unloading rate. This type of analysis also aims to find under what condition the selected scenario will be changed from what was initially chosen. The selected scenario on tactical planning is chosen as a basis, and it is revealed that the selected scenario remains consistent although the ship arrival and operational cost rate is increased. However, the selected best scenario will change when the material type changes and the demurrage rate or target unloading rate increases.**

**Keywords**: *berth allocation problem, demurrage cost, demurrage time, discrete event simulation, operational cost, total port handling cost*

## 1. INTRODUCTION

The berth allocation problem (BAP) which is a major problem in maritime logistics is defined as the allocation of ships at certain docks at certain times during a planning period so that ships can carry out loading and unloading activities (Zhen & Chang, 2012). Furthermore, Bouzekri *et al.* (2021) extend the definition of the BAP as an operational problem to assign ships to berth positions and times to achieve the objective function by considering technical constraints, such as a ship's draft and deadweight tonnage. Generally, berth allocation considers not only the allocation of ships to jetties but also the assignment of other resources, such as conveyors, transportation equipment, cranes, and stockyards. These assignments affect the ship's unloading time, which influences the berth allocation of other ships.

The BAP is a common problem due to uncertainty over weather conditions that affect the ship's travelling time and the loading and unloading processes carried out by workers and equipment at the ports. Therefore, optimising the processes of scheduling, allocation, and other related activities is necessary. Many studies in the literature have discussed the BAP but differed in their assumptions, such as the objective function of the models. Some researchers treat the problem as only berth allocation or integration of subsequent decisions of proper unloading facilities assignments. In addition, the arrival time and processing time per vessel are either deterministic or stochastic, depending on the study. BAP is increasingly complex because of the uncertainty of ships' arrival time, fluctuation in the number of ships, material types, and volume carried. Each material type has unique characteristics affecting the unloading rate. In addition, the rate is influenced by the type of docks. Therefore, the complexity of the BAP is indicated by the interdependence between system components and the uncertainty of ship arrival and unloading duration. As a result, the actual allocation of ships berthing often does not match the predetermined one.

This study aims to evaluate the berth allocation procedures by considering the total port handling costs, which consist of demurrage/despatch costs and dock operational costs, using discrete event simulation (DES). Additionally, this study focuses on the problem of sequencing ships to have berth, which may be considered a variation of the ship-unloading scheduling problem (SUSP) discussed in Gao *et al.* (2021, 2022). Unlike Gao *et al.*, which only considers demurrage costs as the company's existing procedure, the operational cost for berthing is considered since the company uses two kinds of jetties – dedicated and public – which have different unloading costs per tonne of unloaded materials. Another variation is that Gao *et al.* (2021, 2022) assumed that the unloading rates depend on the transferring speed of the belt conveyors. This study extends this by assuming the unloading rates also depend on the materials unloaded. This problem can also be classified as a BAP since this study aims to allocate ships into berths at certain times. Different from other studies, the objective function considers both the operational costs per tonne of unloading materials and demurrage costs per day of excess when comparing the ships' actual departure time and their contract's time.

The contributions of this study are as follows: First, a new variation of the SUSP and BAP is presented with the objective of minimising the total cost, which consists of demurrage cost as a result of excess unloading unit time and operational cost per tonne of unloaded materials. Furthermore, problem of accommodating differences in unloading times for the various materials and facilities will be addressed. Second, this study explores alternative procedures that can be implemented by other companies facing similar problems. In Indonesia, many large industries, not only steel, have dedicated jetties to support their inbound material activities. On some occasions, when the demand is increasing, a company may consider alternatives to utilise public or other company ports to decrease their total unloading costs. Third, the model developed in this paper can be used for operational and strategic decisions. These decisions depend on the data provided. If deterministic data are used, a model can be applied for operational decision-making, while stochastic data are for strategic decisions. Our model is developed in DES to accommodate deterministic and stochastic data. The advantages of DES are its relative ease of incorporation with stochastic data compared with a mathematical model and its accounting for the interaction between components in the systems, such as an interruption in the ongoing ship unloading process due to a change in the production plan. To our knowledge, our DES model is the first model in the literature that can be used for both operational and strategic decisions.

The remaining organisation of this paper is as follows. Section 2 reviews the related literature. The description of the problem is explained in Section 3, followed by model development, verification, and validation in Sections 4 and 5. Section 6 discusses and analyses the results and findings, and finally, Section 7 concludes the paper and offers suggestions for future research.

## 2. LITERATURE REVIEW

Several studies have been carried out to solve and study the problem in the maritime field (Roso *et al.*, 2020; Gurning, 2019; Kurniawan *et al.*, 2022; Setyohadi *et al.*, 2018). Other types of maritime problems include SUSP problem. As previously explained, the problem addressed by this paper can be classified as an SUSP, as defined by Gao *et al.* (2021, 2022). In this problem, based on the data of incoming ships, such as the number of raw materials loaded and the arrival and departure times, the operational plant manager makes decisions on scheduling ships to docks and the types of unloading facilities. The objective of this problem is to find an optimal schedule for the ship unloading activities to decrease the demurrage cost within a prespecified planning horizon.

The BAP generally occurs in terminals with multi-user terminal (MUT) characteristics, namely those used jointly by several shipping lines to carry out loading and unloading activities (Imai *et al.*, 2008). The use of MUTs by shipping lines is due to the increasingly fierce competition between shipping lines as they try to reduce operating costs. One strategy taken by shipping lines to remain competitive is to change loading and unloading activities from a dedicated terminal to an MUT. Additionally, the BAP can be combined with the quay crane allocation problem (QCAP), the laycan allocation problem (LAP), and the quay crane allocation specific problem (QCASP), as discussed by Bouzekri *et al.* (2021).

Most of the reference research also does not really capture the existing port model. Several studies on the BAP employ a mathematical model approach with deterministic assumptions. For example, Golias *et al.* (2009) developed a mixed-integer programming model with the aim of minimising delays and operational costs, using heuristic methods based on genetic algorithms to obtain solutions. However, one weakness of the mathematical model is that it cannot interrupt the ongoing ship unloading process if a change in the production plan occurs. Similarly, Kim *et al.*

(2010) developed a mathematical model to minimise the overall response time consisting of current ship incidents and potential future incidents that may occur at sea. Song *et al*. (2012) developed a model combining static berth allocation and the allocation of quay cranes with the objective function of minimising waiting and handling times. They formulated the problem as a bi-level programming model in which berth allocation is the upper level and crane allocation is the lower level. The lower-level problem was solved using the mixed-integer linear programming method, while the upper-level problem was solved using the genetic algorithm method. Furthermore, Vaferi *et al.* (2018) developed a metaheuristic method to minimise the total distance travelled by considering certain restrictions, such as the capacity of the container ship. Natalia *et al.* (2021) developed a mathematical model to determine the optimal values of containerised cargo and delivery frequency to minimise the total shipping costs.

Another study conducted by Hendriks *et al.* (2013) focused on the problem of simultaneous berth allocation and yard planning at a tactical level through a heuristic approach to reduce the total travel distance of the straddle carrier. Mazioli *et al.* (2019) also conducted mathematical and metaheuristic models to plan port operations and considered despatch and demurrage costs. The developed model aimed to increase the despatch received and reduce the demurrage paid. Tasoglu & Yildiz (2019) created a simulated annealing-based optimisation procedure integrated with a parametric simulation model to minimise the latest ship departure time (makespan). In a relevant study, Karafa *et al.* (2013) conducted research using a heuristic method based on an evolutionary algorithm and a simulation-based Pareto front pruning algorithm with the aim of maximising the throughput of the berth and minimising the risk of the docking schedule.

Previous studies on BAP using the DES method include Henesey *et al*. (2004), who researched using simulation for decision-making in berth assignments to container ships arriving at the container terminal based on a policy to increase capacity at the container terminal by reducing turn-around time. The decision variable used was a priority rule in the form of the shortest turn-around time policy (STTP) or berth closest to stack policy (BCSP). The measured performance parameters were turn-around time and straddle carrier distance travelled. Another simulation model, built by Esmemr *et al.* (2010), aimed to determine the optimal amount of container handling equipment to improve the lean capability of Turkish ports.

Winjarsih & Kromodihardjo (2012) developed a BAP model that only had a parameter/expected output in the form of a total demurrage cost. The decision variable was the number of cranes, and the observed parameter was the queue length, which could be measured based on quay and yard crane utilisation. Budipriyanto *et al.* (2017) also conducted research on the BAP by considering the variability of ship arrivals and service times using DES, which examined the effect of collaboration or terminal cooperation on total handling time and increased utility of resources, such as docks, cranes, and yards simultaneously. In a related study, Lestari & Rachman (2018) used the DES approach to repair demolition activities. The improvement scenario included changes to the resource (number of cranes) to reduce dwelling time activities at the container terminal. López-González *et al.* (2020) conducted terminal expansion experiments to increase system utilisation, including berth, crane, and storage. Their expansion plan included the addition of a pier and storage space. The expansion model was evaluated based on different demand increases.

In addition, several studies have combined various methods. For example, Caceres *et al*. (2015) use the business process model and notation (BPMN) methodology to support the identification and visualisation of processes related to container ships and participants in the process. The research continued with the DES method, producing the primary performance indicators for the process area. Yildirim *et al*. (2020) proposed a decision support system combined with a simulation optimisation module based on the swarm-based artificial bee colony optimisation algorithm to investigate the effect of ship priority on the BAP.

The BAP in this study is a real case in Indonesia in which the company wants to improve the berthing allocation procedure to reduce the total port handling costs. Based on the complex condition of the BAP system, the research uses DES to test the berth allocation procedure and the allocation of loading and unloading facilities.

DES is a simulation method that changes conditions depending on the point in time and the result of an event (discrete), as stated by Robinson *et al.* (2010). Simulations can also imitate the stochastic behaviour of the system and evaluate several possible scenarios in the system without disturbing the actual system, saving time and costs in the evaluation process (Kelton *et al*., 2015). Using the simulation is expected to reduce the risk of losses, assessing alternative decisions while not disrupting the working system. The focus of this research is on designing berth allocation procedures that reduce the total port handling costs with a wider system limit, namely arriving at the cargodoring and receiving processes that affect the berthing start time of the next ship. Our improvement scenario applies several priority methods for selecting docks by considering the parameters of the total port handling costs and ship selection procedures that do not solely focus on first-come-first-serve (FCFS). This procedure can be used by the company at the operational or tactical level. Additionally, our analysis considers the improvement of loading and unloading facilities using simulation and optimisation. Moreover, the parameters used in this study are more comprehensive in terms of both time and cost, while the other studies generally focused on reducing processing time.

# 3. PROBLEM DESCRIPTION

The problem discussed in this paper is inspired by a real logistics problem encountered by a steelmaking company in Indonesia. In this company, the production process requires iron ore in the form of pellets as raw materials imported from other countries. The company uses a free-on-board mechanism in which ships transport materials from one port to another (one-way). Hence, the company pays a fee that depends on the volume of products transported, expressed in tonnes for one voyage (Walderhaug & Hammer, 2007). Additionally, the company must pay an additional fee for any delay in the loading/unloading process from the agreed laycan and laytime, called the demurrage fee. In contrast, if the company can load/unload faster, it earns an incentive, namely dispatch money, which is usually half the demurrage rate (Benarto, 2016). The definition of laycan (laydays and cancellation) and laytime can be found in Bouzekri *et al*. (2021). The laycan starts when a ship arrives at the loading port to begin the loading process, which is carried out by a supplier of the company. Once loading is complete, the ship journeys to the company's destination port. The trip duration may vary depending on the weather and sea current conditions, which can lead to the ship arriving at port not as scheduled.

This study focuses on the unloading activities at the company's port, which include stevedoring, cargodoring and receiving activities. Stevedoring is defined as the activity of unloading goods from the ship to the dock/barge/truck using a ship or land crane, while cargodoring is the activity of transporting goods from the dock to the stacking warehouse using trucks, conveyors, or train cars. Receiving encompasses activities of receiving goods at the warehouse or stacking yard. **Figure 1** shows a visualisation of the company's unloading activities.

As shown in **Figure 1**, the company uses dedicated and public docks. Because of fluctuating demands and uncertain ship arrival times, the company has priority to use a nearby public dock to assist its logistical and operational activities. If the company relies on only the dedicated dock, the logistics process is disrupted, causing the total port handling costs to increase. This public jetty is a dock that can be used by various companies, including the company under study

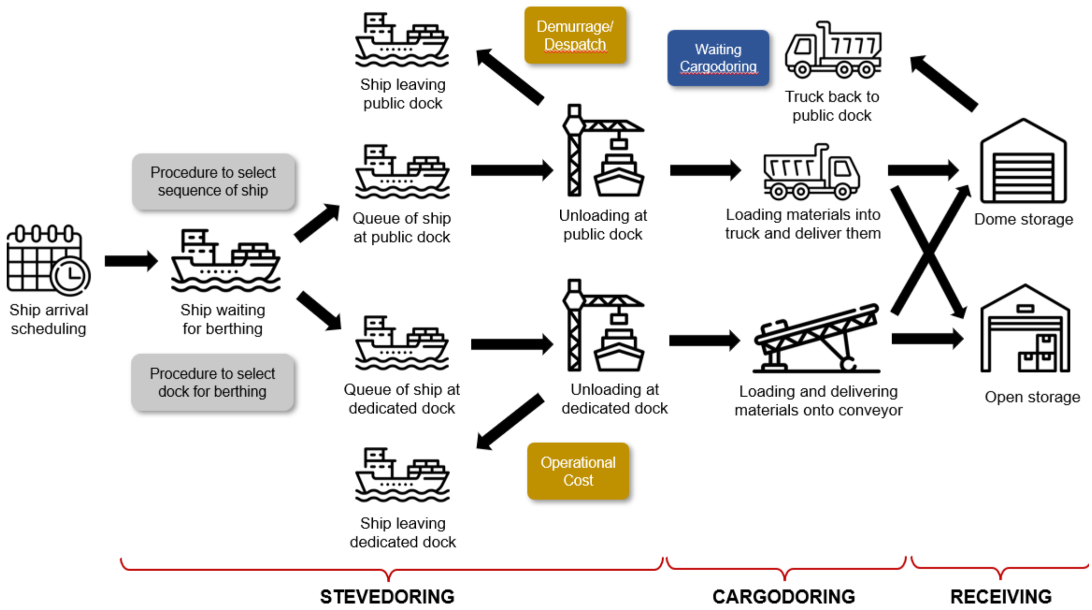


**Figure 1** Visualisation of company's unloading activities

The dedicated and public docks have different capacities and unloading equipment. Both dedicated and public docks use a gantry grab ship unloader. The type of transporters used include conveyors (dedicated dock) and trucks (public dock), and the transporter rate should equal the unloading rate. An imbalance between these can disrupt operations. The transporter rate is affected by the distance between the dock and the stockyard and the speed of transporters. When using docks, the company pays an operational cost (based on volume) and berthing cost, which comprise the total port handling cost that needs to be minimised. An operational decision is made in which the operational department arranges contracts for vessel shipments and their arrivals by considering material availability with the objective to minimise the total unloading cost. In the existing procedure to allocate an arrival ship, a dedicated or public dock is selected based on the lowest forecasted demurrage cost. If two or more ships are in the queue, then the parameters used to choose which ship to be prioritised berthing are based on the highest potential demurrage cost savings.

**Table 1** Design of improvement scenarios

| Scenario | Dock Selection Procedure | | | Ship Selection Procedure | | | |
|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (a) | (b) | (c) | (d) |
| 1 | | | • | | | | • |
| 2 | • | | | | | | • |
| 3 | • | | • | | | | • |
| 4 | | • | | | | | • |
| 5 | | • | • | | | | • |
| 6 | | | • | • | | | |

**Table 2** Design of improvement scenarios (Con't)

| Scenario | Dock Selection Procedure | | | Ship Selection Procedure | | | |
|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (a) | (b) | (c) | (d) |
| 7 | • | | | • | | | |
| 8 | • | | • | • | | | |
| 9 | | • | | • | | | |
| 10 | | • | • | • | | | |
| 11 | | | • | | • | | |
| 12 | • | | | | • | | |
| 13 | • | | • | | • | | |
| 14 | | • | | | • | | |
| 15 | | • | • | | • | | |
| 16 | | | • | | | • | |
| 17 | • | | | | | • | |
| 18 | • | | • | | | • | |
| 19 | | • | | | | • | |
| 20 | | • | • | | | • | |

Of note, all cost-related information is shown in a generic financial unit scaled to maintain confidentiality. However, these values are maintained in terms of their representability towards the real system.

This study aims to find alternative procedures to allocate ships into docks and their docking sequences for the operation decision. The three dock selection procedures are based on (1) the lowest forecast demurrage cost, (2) the lowest forecast total port handling cost, and (3) the shortest queues with priority to the dedicated dock. Meanwhile, the procedure to prioritise ships is based on (a) maximum potential demurrage cost, (b) the largest estimated demurrage rate, (c) the lowest cargo on board, and (d) the first-come-first-serve (FCFS) rule. Combining these dock and ship selection procedures, 20 scenarios are generated, shown in **Tables 1 and 2**, whose performance is assessed in terms of total port handling cost, which is the sum of the demurrage/dispatch and operational/berthing costs.

## 4. MODEL DEVELOPMENT

Our development goal was to create a model that can be used both for operational or tactical decision-making (determining standard operating procedures) and strategic decision-making (determining investments) using DES. To accommodate these two decisions, our single model consists of 16 sub models, and **Figure 2** shows the model configuration. The following explains each sub model within the simulation model developed for this study. The simulation model is run on a device with processor specification 12th Gen Intel(R) Core (TM) i5-1235U 1.30 GHz and 16 GB of RAM.

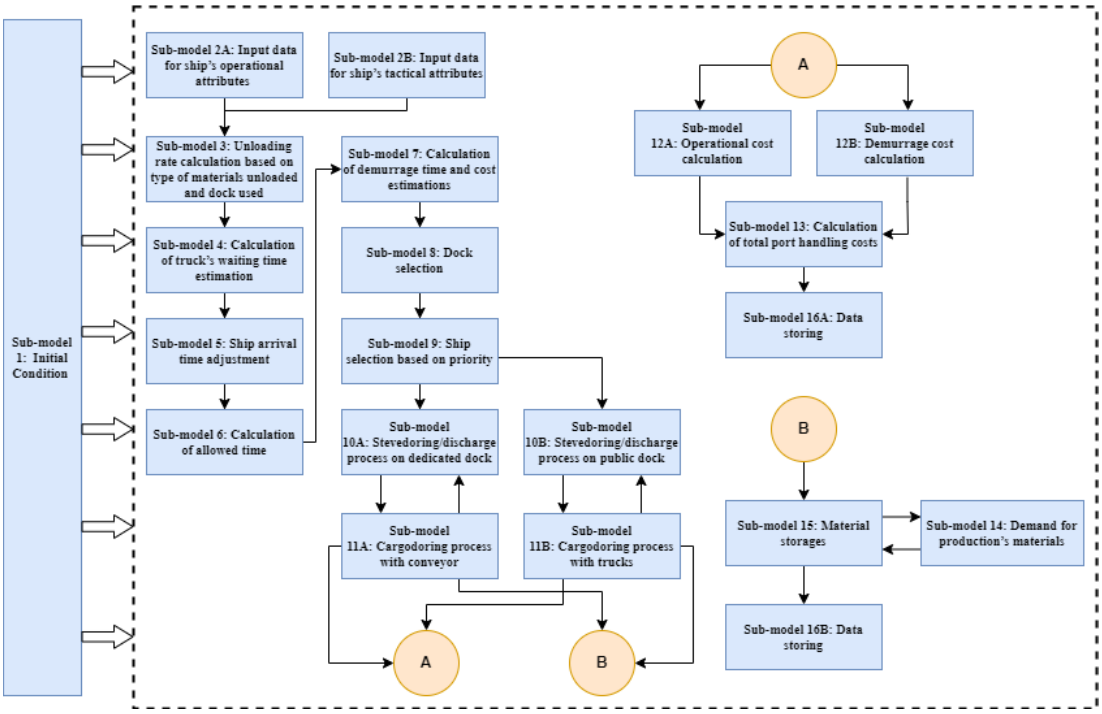

**Figure 2** Sub models in the entire simulation model

### 4.1 Sub Model 1: Initial Condition

The initial condition sub model is run once at the beginning of the simulation. The sub model is developed to generate a series of initial conditions, such as ship arrival, operational cost for each dock, number of trucks, and stockyard's maximum capacity. The logic flow diagram of this sub model is shown in Appendix 1.

### 4.2 Sub Model 2: Input Data for Operational and Tactical Attributes

Operational data, which are deterministic, are obtained by linking the simulation model to a spreadsheet. In contrast, tactical data, which are stochastic, are obtained from distribution fitting. Both operational and tactical data include attributes such as arrival time, material type, volume of load, demurrage rate, and unloading rate target. The logic of sub model 2 is explained in Appendix 2.

### 4.3 Sub Model 3: Unloading Rate Calculation

The unloading rate depends on the material type and dock where the ship is being unloaded. The unloading rate affects the unloading duration of each ship, impacting the total time, which is later adjusted to the "allowed time" (Sub model 6) to determine whether the ship will experience demurrage. Appendix 3 exhibits the logic of this sub model.

### 4.4 Sub Model 4: Estimated Truck Waiting Time Calculation

Truck waiting time is obtained when the total time for loading the maximum number of trucks used by the company is less than the total time for each truck to complete cargo delivery to the storage and return to the public dock. This waiting time is required to calculate forecast demurrage cost, which is later used in dock selection. The sub model's logic is shown in Appendix 4.

### 4.5 Sub Model 5: Ship Arrival Time Adjustment

Ship arrival depends on what data are being used. If operational data (from the spreadsheet) are employed, the adjustment takes place by updating the arrival time attribute to equal the simulation time in the simulation software. The logic flow diagram for sub model 5 is presented in Appendix 5.

### 4.6 Sub Model 6: Allowed Time Calculation

Demurrage cost depends on the allowed time of each ship. The logic applied for this sub model is shown in Appendix 6. The calculation of allowed time differs because of several conditions, as shown in **Figure 3**. The different condition is related to 3 key aspects namely berthing time (BT), waiting time (WT), and turn time (TT) where it will be inspected whether the total of BT and WT is less than, more than or equal to TT.

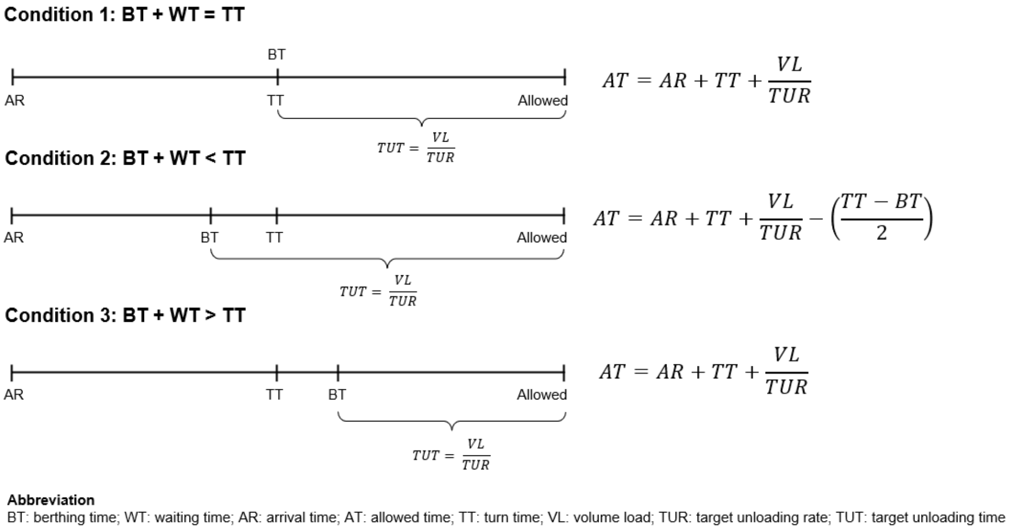


**Figure 3** Different conditions in calculating allowed time

### 4.7 Sub Model 7: Forecast Demurrage Time and Cost Calculation

Demurrage time is necessary to calculate since it is used to determine the forecasted demurrage cost. Conditions involved in calculating demurrage time include forecasted waiting time and queue conditions at the dock. Once the demurrage time is determined, the demurrage cost can be calculated. If the demurrage time is positive, then the demurrage cost is calculated by multiplying the demurrage time by the demurrage rate. In contrast, when demurrage time is zero (on time) or negative (faster), then despatch occurs. The logic of sub model 7 is presented in Appendix 7.

### 4.8 Sub Model 8: Dock Selection

The forecasted demurrage cost is used as the basis for selecting a dock. In addition, the dock capacity is considered in dock selection. The maximum load that can be processed in a public dock is 66,000 tonnes. Once the load exceeds that capacity, a dedicated dock should be allocated. The sub model's logic is shown in Appendix 8.

### 4.9 Sub Model 9: Ship Selection

In selecting which ship to unload, the dock must first be confirmed available since each dock can only process one ship at a time. Then, the selection of which ship to process first is based on which ship has the maximum potential demurrage cost. Appendix 9 exhibits the logic of sub model 9.

### 4.10 Sub Model 10: Stevedoring Process

When a ship starts its process at the dock, the queue variable is updated for the purpose of forecasted waiting time and cost of the following ship. The ship that is selected based on the procedure is processed (berthing, unloading, departure) using the existing facilities. Once that ship departs, another ship is allowed to enter the dock. The stevedoring process differs in public and dedicated docks. In the public dock, when no truck available is available or the truck is delivering material to the stockyard, the ship is required to wait until a truck returns. On the other hand, a conveyor is utilised at a dedicated dock to assist in the stevedoring process. To get the better understanding of how this sub model works, Appendix 10 is provided to give a clearer information.

### 4.11 Sub Model 11: Cargodoring Process.

As mentioned earlier, at a dedicated dock, a conveyor is used to transport material, which is unloaded by a crane directly to the stockyard. Meanwhile, at a public dock, the cargodoring process relies on trucks that receive unloaded materials from the ship, transport them to the stockyard, unload them at the stockyard, and travel back to the dock to receive another load to transport. Appendix 11 is provided to give better understanding regarding logic of this sub model.

### 4.12 Sub Model 12: Operational & Demurrage/Despatch Cost Calculations

The operational cost is obtained by multiplying the volume load of each ship by the tonnage rate of the dock. Of note, the tonnage rate of a dedicated dock is lower (i.e., less expensive) than that of a public dock. To calculate the demurrage cost, the demurrage duration has to be assessed. If the demurrage time is positive, then the demurrage cost is obtained by multiplying the demurrage time by the demurrage rate. In contrast, when the demurrage time is zero or negative, then a despatch cost is earned at half the demurrage time multiplied by the demurrage rate. Appendix 12 is presented to deliver a better understanding of this sub model.

### 4.13 Sub Model 13: Total Port Handling Cost Calculation

By obtaining both operational and demurrage/despatch costs, the total port handling cost can be calculated by summing these components. The process that occurs in sub model 13 is shown in Appendix 13.

### 4.14 Sub Model 14: Material Demand

The material demand sub model accounts for the demand for raw material necessary to perform production activities. Production cannot be carried out if the available inventory is less than the demand. The logic flow diagram of sub model 14 is provided in Appendix 14.

### 4.15 Sub Model 15: Material Storage at Stockyard

The storage of material types is divided into two places, namely dome and open storages, which are allocated to certain materials. Each material-type storage has the same total storage capacity. Appendix 15 presents the logic of this sub model.

### 4.16 Sub Model 16: Data Storing

Recorded data consists of arrival time, allowed time, forecasted demurrage time, forecasted demurrage cost, dock of choice, demurrage cost, and total port handling cost. The data of each ship are recorded automatically in a spreadsheet that the company can use as a logistic system database. Appendix 16 is provided to talk about this sub model.

## 5. MODEL VERIFICATION AND VALIDATION

A model needs verification and validation to ensure that the model represents the real system. Verification indicates that the conceptual model has been transformed into a computer model with sufficient accuracy, while model validation is the process of determining whether the conceptual model correctly reflects the real system.

### 5.1 Model Verification

The model in this study is verified via two methods: syntax and semantics. The syntax error is assessed to ensure that a simulation model does not contain character typographical errors or other quantitative input that can cause failure in executing the simulation model. This type of verification is carried out by exploiting a debug feature within the simulation software.

Semantic verification ensures the model runs according to the desired function and in accordance with the flow/logic of the conceptual model. The three semantic verifications performed in this study are (1) confirming the number of incoming ships, (2) verifying the berth allocation procedure, and (3) checking the ship selection allocation. The animation feature of the simulation software is utilised to conduct semantic verification.

**Table 3** Validation result

| Statistics | Total Port Handling Cost | | Total Operational Cost | | Total Demurrage and Despatch Cost | |
|---|---|---|---|---|---|---|
| | *Real System* | *Simulation* | *Real System* | *Simulation* | *Real System* | *Simulation* |
| *Mean* | 23.30 | 21.32 | 21.44 | 19.52 | 1.86 | 1.80 |
| *n* | 1 | 13 | 1 | 13 | 1 | 13 |
| *St. Dev.* | 0.00 | 1.76 | 0.00 | 1.38 | 0.00 | 0.68 |
| *p-value* | 0.5506 | | 0.3536 | | 0.9030 | |
| *Conclusion* | *p-value* > *α* | | *p-value* > *α* | | *p-value* > *α* | |

### 5.2 Model Validation

Model validation is carried out using the *t-test* method by comparing the *t-test* value obtained from the simulation against the *t-critical* value. Three parameters are compared: total port handling cost, operational cost, and demurrage cost. The model is validated when all *t-test* values do not fall in the rejection area. Hence, no sufficient evidence indicates that the simulation model is different from the real system. **Table 2** is presented as validation evidence.

### 5.3 Number of Replications

The nature of simulation is random input–random output (RIRO), or in other words, the input from the simulation is random, so the output generated is also random. Therefore, replicating the simulation experiments was necessary to overcome the characteristics of RIRO and the variability of the output so that the model is representative of the real system. The data used to determine the number of required replications are the total port handling costs and operational costs, the main performance parameters in this study. In determining number of replications, the parameter namely half-width is used (Harrell *et al*., 2004). There are 2 types of half-width that are used which are actual half-width (*hw*) obtained from simulation model and expected half-width (*hw*') acquired from calculation by setting the expected error rate. The replication number is said to be sufficient if condition $hw < hw'$ is satisfied. Otherwise, the number of replications should be added to reach the expected half-width.

Initially, the simulation model was run with 10 replications and a 95% confidence level. These experiments are intended to determine the actual number of replications needed. Based on the result, it is obtained that $hw > hw'$. Therefore, it is concluded that 10 replications in running simulation model is not sufficient to represent the actual system. The calculation of the experiment results shows that the minimum number of replications needed so that the simulation model could reflect the actual system is 13 replications. Therefore, the existing simulation models and scenarios are run with 13 replications.

## 6. RESULTS AND ANALYSIS

This section interprets the research results and the existing-condition, improvement-scenario, and sensitivity analyses.

### 6.1 Existing Condition Analysis

In simulating the existing conditions, the main performance metric is the total port handling cost, which consists of operational and demurrage/despatch costs. The metric is influenced by various factors, such as dock and ship selection in the BAP, ship arrivals uncertainty, demurrage rates, volume load, and material type. In the existing BAP procedure, the dock is selected based on the lowest forecasted demurrage cost, while ship selection is based on the largest demurrage cost.

The simulation run for one year with 13 replications shows that in the existing condition, the average total port handling cost incurred by the company for one year is 21.318 financial units. The components that make up the total port handling costs are operational costs of 19.521 financial units and demurrage costs of 1.797 financial units. **Figure 4** shows the detail of the cost incurred per replication. The demurrage cost appears because some ships exceed the agreed allowed time or laytime. According to the simulation of one year, on average, 71% of ships unloaded exceed the agreed laytime. The ideal condition expected by the company is the absence of demurrage. However, since this demurrage takes place, the company spend additional costs on the demurrage rate, which increases the overall port handling cost.

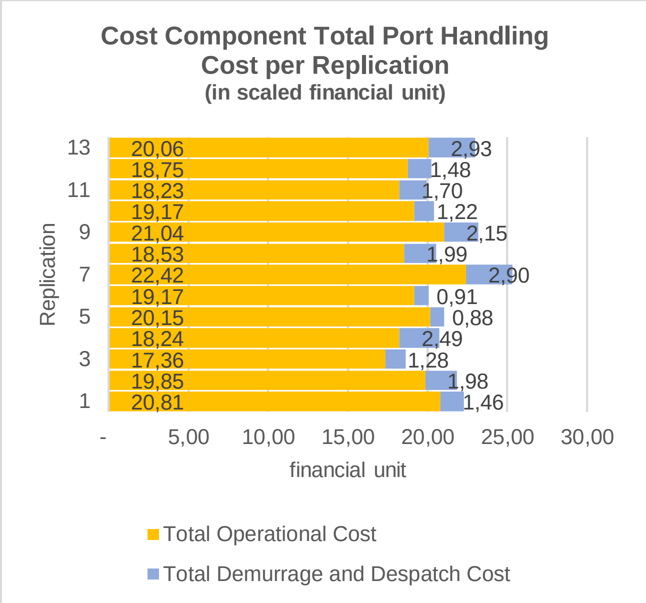


**Figure 4** Detail of cost component of total port handling cost per replication

Of note, ships arriving at almost the same time when docks are being used also incur high demurrage costs. On average, 84% of ships arrive when the dock is still in use. The average total waiting time of ships in a year is 5,608.2 h, while the demurrage time is 4,471.6 h per year. As mentioned earlier, using public docks is more costly than dedicated docks, significantly affecting the operational cost. Based on simulation, only 71% of ships are served using the dedicated dock, while the remaining 29% are at the public dock.

In the BAP, the dock and ship selections are interrelated, and the procedure is expected to yield the least cost. Unfortunately, in this case, the company still incurs high operational and demurrage costs. The existence of demurrage costs hurts the company financially. Therefore, evaluating the berth allocation procedure is necessary. In addition, unloading facilities to carry out tactical (long-term) planning is necessary to assess. These two tasks help determine an effective way to significantly reduce the total port handling cost.

### 6.2 Improvement Scenario Analysis

The improvement scenario is carried out through two stages. The first is operational planning, which is for daily or monthly planning, using definite data or a deterministic approach, and the same number of unloading facilities as the existing conditions are used to reveal the better procedure. The second stage is tactical planning, which is for long-term planning, using a stochastic approach and in accordance with the improvement of unloading facilities. Both stages seek the lower total port handling cost. The improvement scenarios are shown in **Table 1**.

*6.2.1 Operational Planning Analysis*

Among the 20 experimentations using deterministic data, Scenario 12, which consists of a dock selection procedure based on the lowest demurrage cost estimation and a ship selection procedure based on the maximum demurrage rate, yields a lower total port handling cost than the existing one. **Figure 5** shows a comparison of the total port handling costs between scenarios.

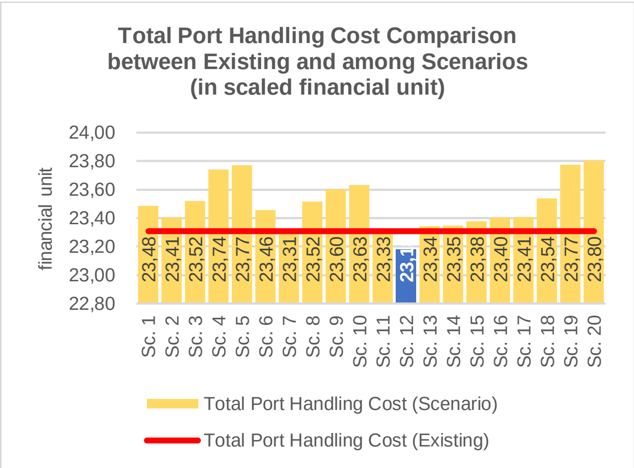


**Figure 5** Comparison of total port handling costs between scenarios (operational)

This cost reduction is obtained only from the reduction of the total demurrage and despatch costs because of the reduced demurrage time of 419.29 h from the existing condition. The total operational cost does not change in Scenario 12 because it uses the same current dock selection procedure. **Figure 6** shows a comparison of the total operational cost of each scenario and the existing conditions.

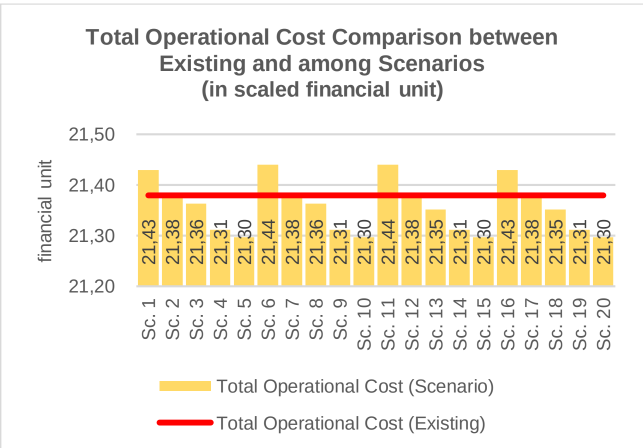


**Figure 6** Comparison of total operational costs between scenarios (operational)

**Figure 6** indicates that the dock selection procedure affects the total operational cost with the same pattern. Higher operational costs result from Scenarios 1, 6, 11, and 16, whose dock selection procedure is based on the priority of using the dedicated dock. Meanwhile, the lowest operational costs are indicated by Scenarios 5, 10, 15, and 20, which share the same dock selection procedure based on the lowest forecasted total port handling cost and priority to the dedicated dock.

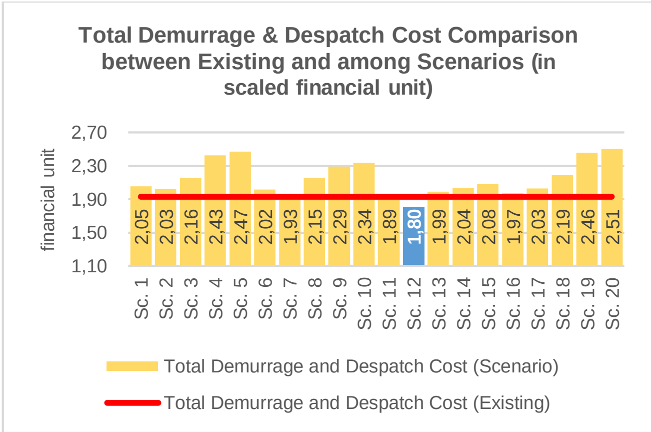


**Figure 7** Comparison of total demurrage/despatch costs between scenarios (operational)

From **Figure 7**, the procedure based on the lowest demurrage cost forecast is the most optimal of dock selection procedures in terms of decreasing the total demurrage/despatch costs. However, overall, the best ship selection procedure to reduce the total demurrage/despatch costs is based on the maximum demurrage rate. From the results, Scenario 12 has the lowest total demurrage/despatch cost because of a change in the ship selection procedure, which was originally based on the maximum potential demurrage cost and maximum demurrage rate. The decrease in total demurrage/despatch cost when using the ship selection procedure based on the maximum demurrage rate compared to the existing procedure is 0.125 financial units.

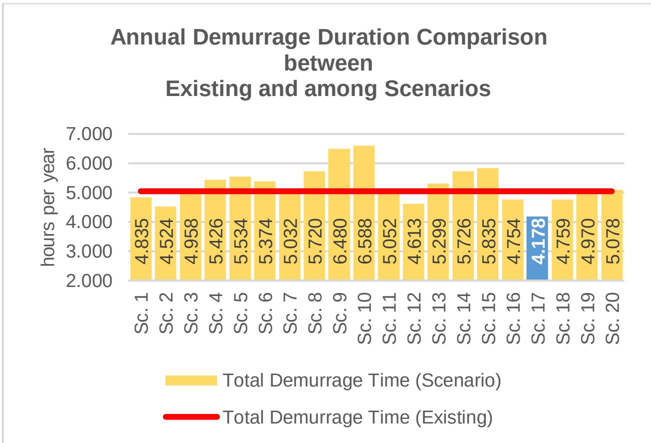


**Figure 8** Comparison of total demurrage duration between scenarios (operational)

The pattern of decreasing total demurrage and despatch costs is influenced by the decrease in total demurrage time. **Figure 8** shows that in all conditions, the procedure that yields the shortest demurrage time is when the ship selection procedure is based on the minimum volume of cargo, as shown by Scenario 17, which results in a demurrage duration of 4,178 h per year. However, although Scenario 17 has the shortest demurrage duration, its cost is not the least. Rather, Scenario 12 yields the lowest cost among all scenarios for operational planning.

*6.2.2 Tactical Planning Analysis*

In tactical planning, the optimisation of the number of loading and unloading facilities is carried out for each scenario with a fitting distribution of uncertainty data, which includes the interarrival time of each ship, number of shiploads, type of shipload materials, and demurrage rate. Optimisation is performed to minimise the total port handling costs for the next one-year planning horizon. **Table 3** and **Table 4** shows the optimisation results for the facility allocations.

Once the optimum number of facilities assigned at the dock is obtained, performance of each scenario will be compared based on the metrics. **Figure 9** shows a comparison of the total port handling cost between the existing condition and scenarios on tactical planning. All scenarios yield lower total port handling costs, implying that additional unloading facilities, especially cranes, significantly reduce the total port handling cost. However, Scenario 2, with the dock selection based on the lowest forecasted demurrage cost, ship selection following the FCFS rule, and two cranes allocated on both the dedicated and public docks with nine trucks, yields the lowest total port handling cost. With a total annual cost of 18.105 financial units, the company can reduce costs by 15.05% compared to the existing condition.

**Table 4** Optimum number of allocated facilities for each scenario (existing, scenario 1-10)

| Facility | Scenario | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| | Exist. | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
| *Crane at Dedicated Port* | 1 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 |
| *Crane at Public Port* | 1 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 |
| *Trucks* | 8 | 10 | 9 | 9 | 10 | 8 | 10 | 9 | 8 | 9 | 8 |

**Table 5** Optimum number of allocated facilities for each scenario (existing, scenario 11-20)

| Facility | Scenario | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | 11 | 12 | 13 | 14 | 15 | 16 | 17 | 18 | 19 | 20 |
| *Crane at Dedicated Port* | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 |
| *Crane at Public Port* | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 | 2 |
| *Trucks* | 10 | 8 | 9 | 8 | 8 | 9 | 8 | 9 | 10 | 8 |

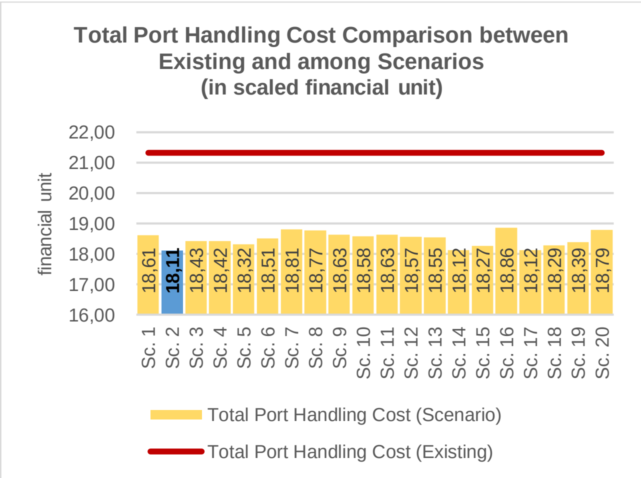


**Figure 9** Comparison of total port handling costs between scenarios (tactical)

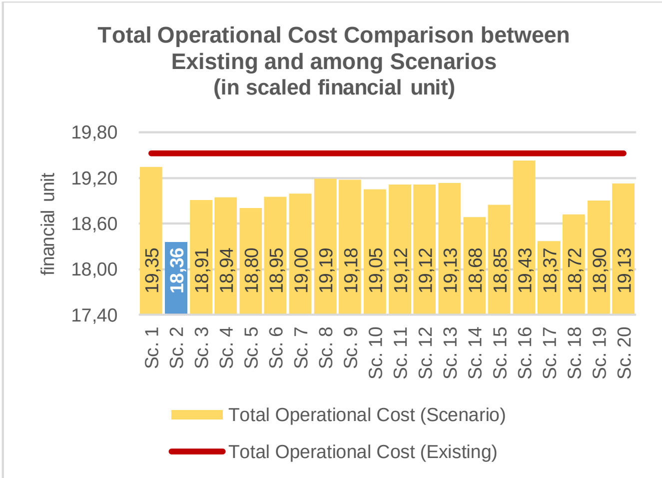


**Figure 10** Comparison of total operational costs between scenarios (tactical)

Furthermore, the performance of scenarios is assessed based on the components that comprise the total port handling cost. **Figure 10** shows a comparison of operational costs among the existing condition and developed scenarios. By applying the dock selection based on the lowest forecasted demurrage cost, Scenario 2 has the best performance, marked by the lowest operational cost. By applying such a procedure, ships are mostly allocated to the dedicated dock, increasing the proportion of ships using the dedicated dock from 71% in the existing condition to 85%. The reduction in cost for Scenario 2 is 5.97%, followed by Scenario 17 with 5.89%.

**Figure 11** shows the scenarios' performance in terms of demurrage/despatch costs. Additional unloading facilities can cut the demurrage time significantly; hence, the ship can be served faster and earlier than the agreed laytime. **Figure 11** shows this finding in which all scenarios have negative values of demurrage costs, which means the company gains the despatch money from serving the ship with durations shorter than the agreed laytime. Scenario 1 yields the largest despatch earnings among the scenarios, with a value of 0.736 financial units gained per year. Scenario 2, which has the lowest total port handling cost, only gains 0.246 financial units of despatch annually. However, Scenario 2 can reduce the total annual waiting time by 63% to 2,094 h and demurrage time by 150% to −2,228 h. In other words, in a year, all ships can be served in 2,228 fewer hours than the laytime. This finding is also strengthened by the fact that the percentage of ships exceeding their laytime decreases from 71% to only 27%.

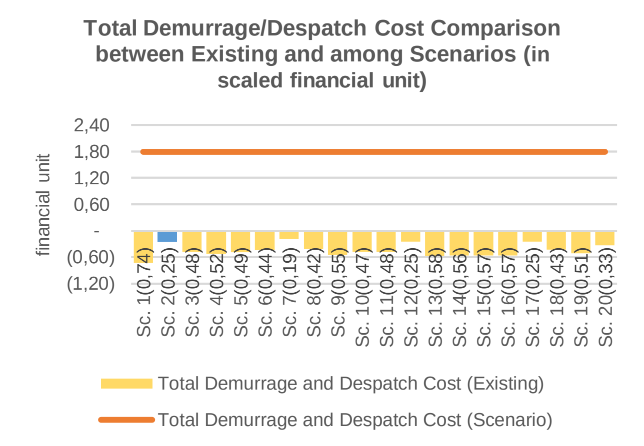


**Figure 11** Comparison of total demurrage/despatch costs between scenarios (tactical)

## 6.3 Sensitivity Analysis

A sensitivity analysis is carried out to test the robustness of the model and check the extent to which the selected scenario is still feasible. In this case, Scenario 2 in tactical planning is used as the normal condition. To perform the sensitivity analysis, alterations in five parameters generate five conditions. These parameters include the incoming material type, number of ships arriving, demurrage rate, target unloading rate, and operational cost. In this step, it will be check if Scenario 2 still comes out as the selected best scenario once there is a change in one of those five parameters.

### *6.3.1 Condition 1: Only One Material Type*

In this condition, only one type of material, type 1, is carried by the ship. The volume of material type 1 dramatically increases, which affects the operational cost. Based on this condition, Scenario 1 is the best alternative with the lowest total port handling cost. Prioritising the usage of the dedicated dock, this scenario results in a low operational cost and high unloading rate. Therefore, it can be concluded that if there is only one type of material, Scenario 2 will no longer feasible and Scenario 1 comes out as the best scenario when this condition takes place.

### *6.3.2 Condition 2: Ship Arrival Increases by 20%*

As the number of arriving ships increases, the volume load increases, leading to higher operational costs. Furthermore, the chance of ships arriving at the same time is higher, causing higher demurrage costs. In this condition, Scenario 2 performs the best, where the dock selection is based on the lowest forecasted demurrage cost. By applying this scenario, the company can suppress the total port handling cost, especially one coming from demurrage/despatch cost. Hence, when the increase in ship arrival happens, Scenario 2 still comes out as the best scenario and is feasible under this condition.

### *6.3.3 Condition 3: Demurrage Rate Increases by Five Times*

The next condition is when the demurrage rate increases by 500%. This will drastically increase the total port handling cost overall. By applying this condition, Scenario 1 is the best solution, whose dock selection procedure is based on dedicated dock usage prioritisation, enabling the company to carry out the unloading process faster since the location of the dedicated dock is close to the production facility and it has a higher unloading rate. In this case, the chance of demurrage occurring decreases, improving the probability of despatch. It can be inferred that when the demurrage rate is increased five-fold, Scenario 2 is no longer feasible as the best scenario. Instead, Scenario 1 appears as the wisest option to suppress the total operational cost given this circumstance.

### *6.3.4 Condition 4: Target Unloading Rate Increases by 10%*

Increasing the target unloading rate by 10% causes the laytime to shorten. The shorter laytime leads to a higher probability of demurrage since a ship has a narrower allowable timespan to be served at the dock. With this condition, the simulation result suggests that Scenario 17 is suitable to overcome this situation. Scenario 17 uses the lowest forecasted demurrage cost for dock selection and minimum volume load for ship selection. As a result, the demurrage cost and, hence, the total port handling cost are minimised. Like previous condition, Scenario 2 will no longer be feasible option when the target unloading rate is increased by 10%. Scenario 17 replaces Scenario 2 as the best scenario when this condition occurs.

### *6.3.5 Condition 5: Operational Cost Increases 10%*

In Condition 5, operational cost rate is increased by 10%. Intuitively, increasing this rate also increases the total operational cost. Hence, according to the simulation result, Scenario 2 is preferable when this situation arises. Since Scenario 2 uses the lowest forecasted demurrage cost as a basis to select the dock, it aims to minimise and suppress the total port handling cost that comes from demurrage/despatch cost. Therefore, Scenario 2 is still chosen as the best scenario when there is 10% increase on operational cost rate.

### *6.3.6 Sensitivity Analysis Summary*

**Table 5** below summarises the sensitivity analysis results. Scenario 2 of tactical planning is taken as the basis of comparison. Sensitivity analysis aims to check if Scenario 2 is still feasible and comes out as the best scenario when some parameters or conditions are changed. In summary, Scenario 2 stays feasible and appears as the best scenario when either ship arrival or operational cost rate is increased. However, the best scenario is switched significantly from Scenario 2 to Scenario 1 when there is only one type of raw material and demurrage rate is multiplied by 5 times. Lastly, the best scenario also seems to change from Scenario 2 to Scenario 17 once there is an increase in target unloading rate by 10%. In conclusion, the best scenario in tactical planning seems robust under certain circumstances. However, when other condition such as material type, demurrage rate, and target unloading rate is changed, the best scenario taken should be different from one that is initially chosen.

**Table 6** Summary of sensitivity analysis results

| Condition | Alteration | Impact | Best Scenario | Berth Allocation Procedure | | Number of Unloading Facilities at Berth | | | Rationale |
|---|---|---|---|---|---|---|---|---|---|
| | | | | Dock Selection | Ship Selection | Crane - Dedicated | Crane - Public | Truck | |
| 0 (Normal) | - | - | 2 | Lowest forecasted demurrage cost | FCFS | 2 | 2 | 9 | Reducing total port handling cost by suppressing total demurrage/despat ch cost |
| 1 | Material type (only 1 type) | Volume load increases, causing operational cost increases. | 1 | Shortest queues with priority to dedicated dock | FCFS | 2 | 2 | 10 | Using a dedicated dock to incur the company less operational cost and increase the unloading rate |
| 2 | Ship arrival (+20%) | Volume load increases causing operational cost increases, increasing the probability of ships arriving at the same time as well as the demurrage cost. | 2 | Lowest forecasted demurrage cost | FCFS | 2 | 2 | 9 | Reducing total port handling cost by suppressing total demurrage/despat ch cost |
| 3 | Demurrag e rate (500%) | Higher demurrage cost causes the total handling cost to increase. | 1 | Shortest queues with priority to dedicated dock | FCFS | 2 | 2 | 10 | Unloading at a dedicated dock to increase the unloading rate, reducing the chance of demurrage and possibly despatching the ship earlier |
| 4 | Target unloading rate (+10%) | Narrower laytime leads to a higher chance of demurrage. | 17 | Lowest forecasted demurrage cost | Minimum volume of load | 2 | 2 | 8 | Gaining the lowest demurrage cost |
| 5 | Operation al cost (+10%) | Total operational cost is increased. | 2 | Lowest forecasted demurrage cost | FCFS | 2 | 2 | 9 | Reducing total port handling cost by suppressing total demurrage/ despatch cost |

# 7. CONCLUSIONS AND SUGGESTIONS

The BAP is a significant challenge faced by various companies, especially those requiring maritime logistics. The BAP is concerned with the procedure of dock allocation as well as ship or vessel selection. Both procedures should be formulated properly so that the total port handling cost can be minimised. The total port handling cost consists of operational cost, which is heavily related to the volume load of ships and the type of dock, and demurrage cost, which is affected by the duration of ships at the dock. This paper considers a real-world problem inspired by a steelmaking company in Indonesia. This company uses two types of ports to receive their raw materials: public dock (shared with other companies) and dedicated dock (privately owned by this company). The company currently follows the lowest forecasted demurrage cost to select the dock and the maximum potential demurrage cost in prioritising ships to serve.

This study aims to evaluate the berth allocation procedure of the company. Because of the complexity of the system caused by interdependencies among system components and the uncertainty, DES is employed. The simulation result of the existing condition indicates that the annual total port handling cost is 21.318 financial units, which consists of an operational cost of 19.521 financial units and a demurrage cost of 1.797 financial units. Next, several improvement scenarios were developed by combining three procedures for dock selection and four procedures for ship selection, totalling 20 scenarios. Two types of improvement analysis are carried out, namely operational planning analysis, which heavily relies on deterministic data, and tactical operational planning analysis, which exploits a stochastic approach.

Based on the operational planning analysis, Scenario 12, in which dock selection is based on the lowest forecasted demurrage cost while ship selection is based on the largest estimated demurrage rate, is preferable, as indicated by the total port handling cost reduction of 0.125 financial units annually. In tactical planning, number of facilities allocated at the unloading facility is optimized. Adding unloading facilities, such as cranes and trucks, significantly reduces the total port handling cost. This case applies to all the scenarios developed. However, Scenario 2, which uses the lowest forecasted demurrage cost and FCFS rule for the procedure of dock and ship selection, respectively, performs the best among the scenarios because of its lowest total port handling cost. This scenario successfully reduces the total handling cost by 15% annually. Sensitivity analysis is also performed to test the robustness of the model and identify the condition when the selected scenario becomes infeasible. The analysis was carried out by modifying five parameters: material type, ship arrival rate, demurrage rate, target unloading rate, and operational cost. Various result is reported on sensitivity analysis. Scenario 1 suits the best when only one type of material or the demurrage rate is increased five times. When there are increases in ship arrival rate and operational cost rate, Scenario 2 comes out as the best alternative. Lastly, it is preferable to apply Scenario 17 when the target unloading rate increases.

This study was performed by neglecting the parameter of minimum inventory available at the stockyard as well as assuming that all unloading facilities never experience a breakdown. Therefore, for future research, it is recommended considering the minimum inventory of raw materials at the stockyard which affects the strategy to take. Additionally, considering the maintenance time and failure rate of berth unloading facilities may enrich this research to better approach the real system. This study also limits its scope by neglecting the facility investment cost. It is suggested to consider the investment cost in the future research so that the decision making will be better by considering the cost aspect.

# ACKNOWLEDGEMENT

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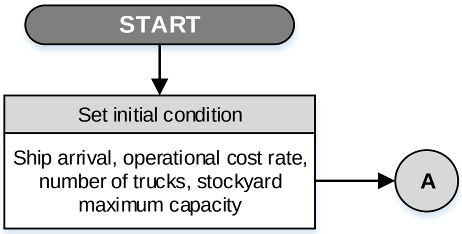
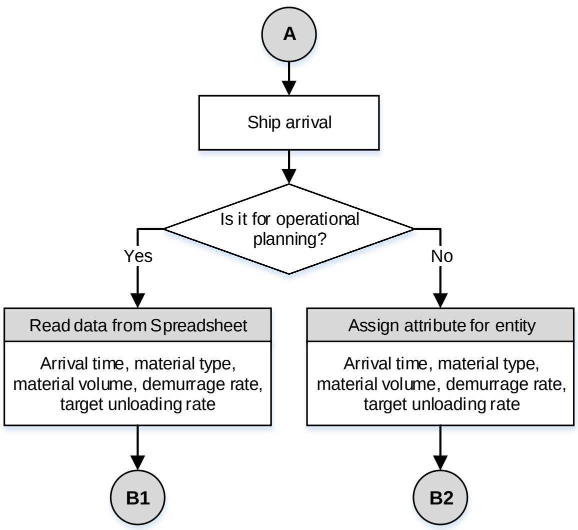
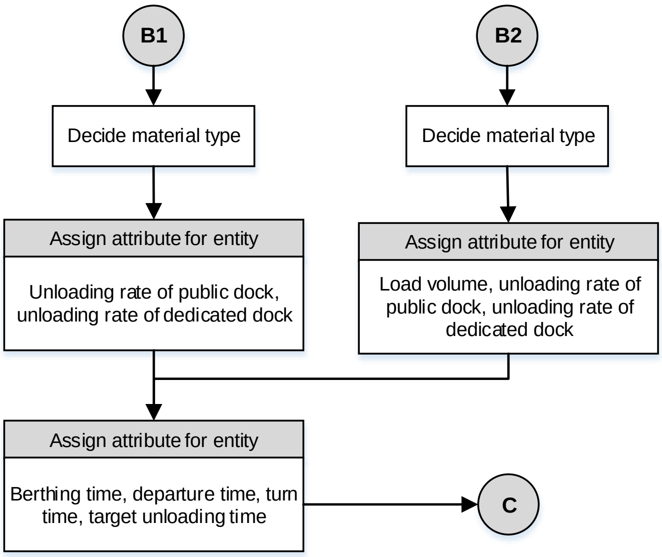
# APPENDIX 1: LOGIC FLOW OF SUB MODEL 1



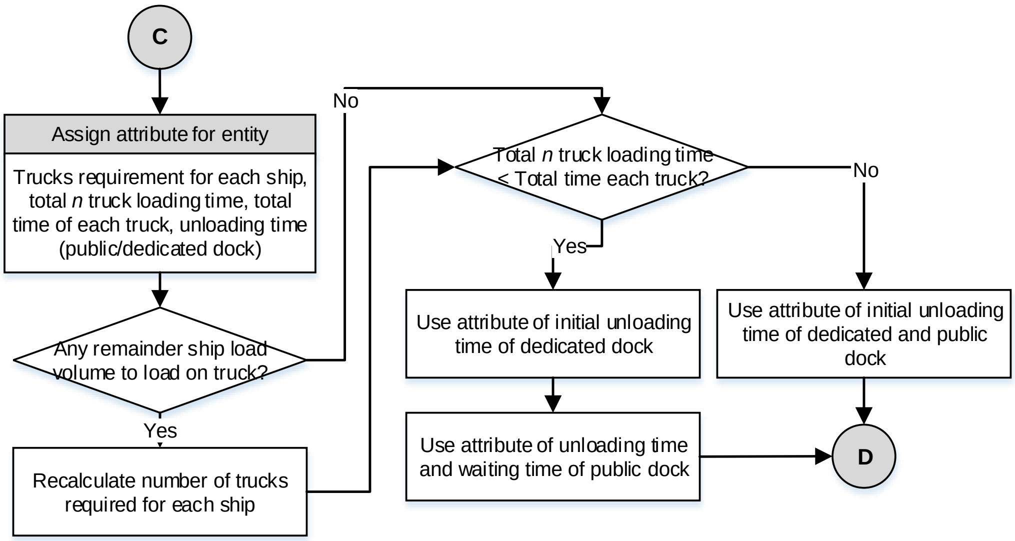

# APPENDIX 2: LOGIC FLOW OF SUB MODEL 2



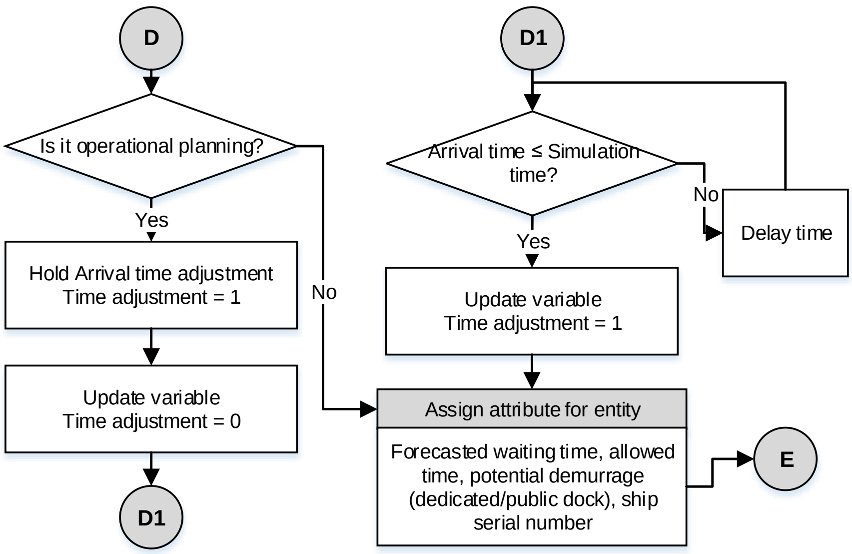

# APPENDIX 3: LOGIC FLOW OF SUB MODEL 3



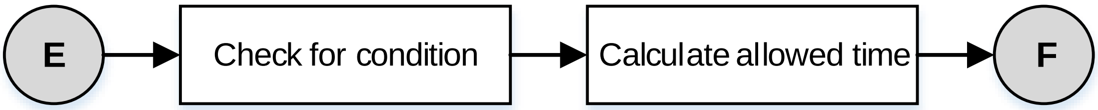

## APPENDIX 4: LOGIC FLOW OF SUB MODEL 4



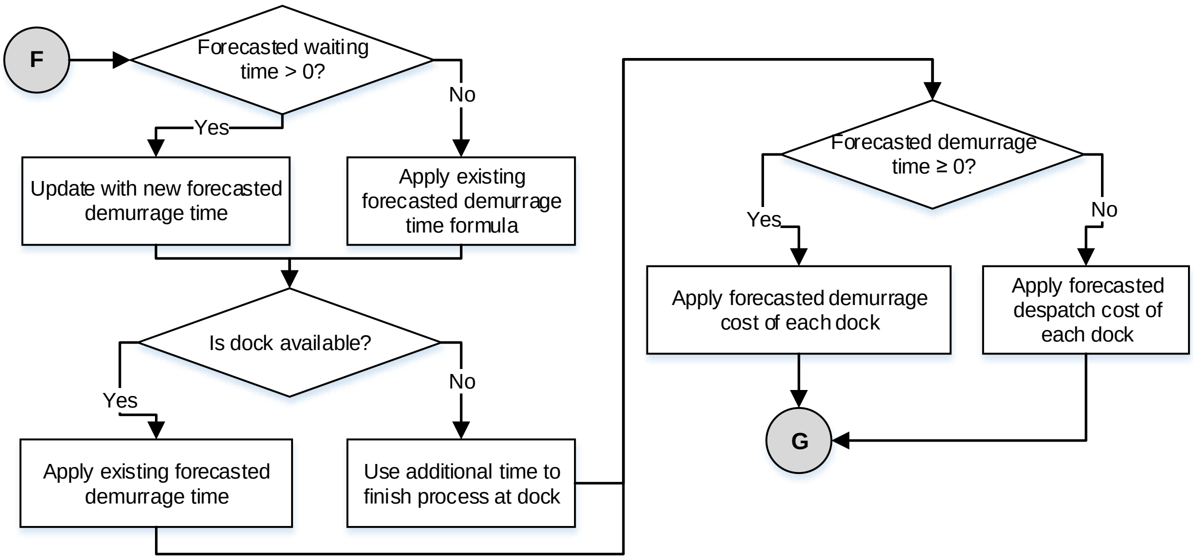

## APPENDIX 5: LOGIC FLOW OF SUB MODEL 5



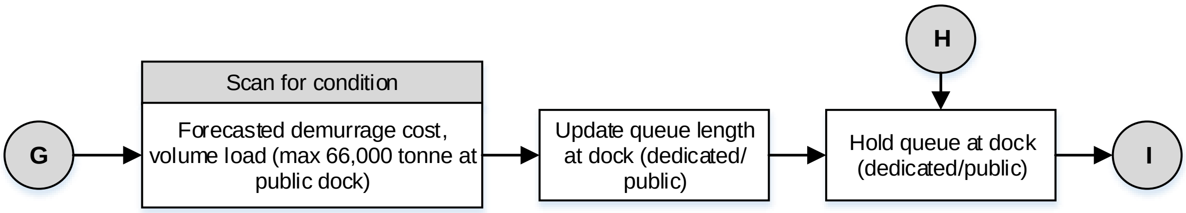

## APPENDIX 6: LOGIC FLOW OF SUB MODEL 6



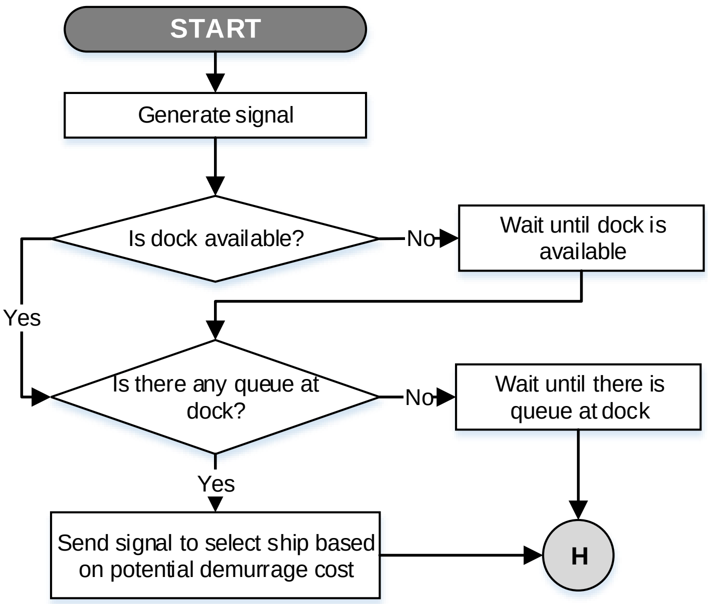

## APPENDIX 7: LOGIC FLOW OF SUB MODEL 7



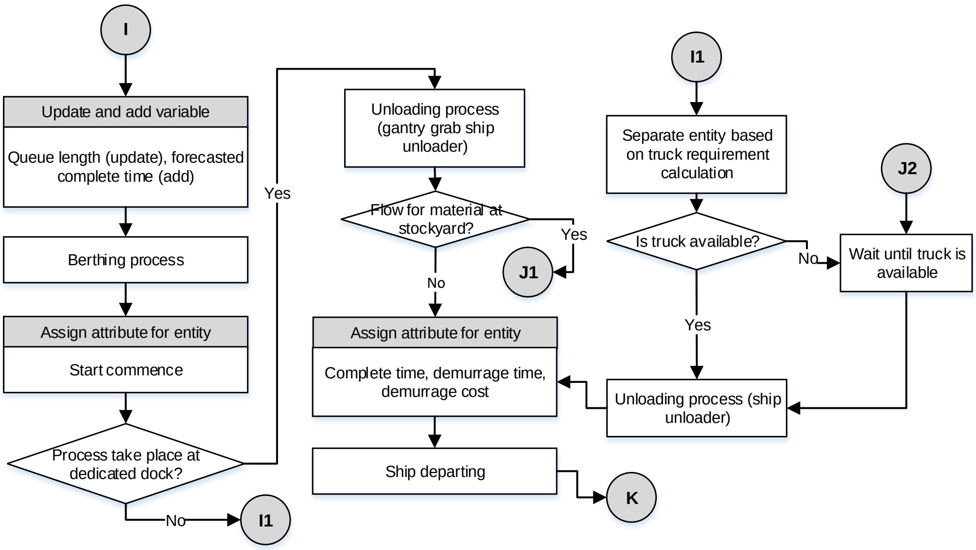

## APPENDIX 8: LOGIC FLOW OF SUB MODEL 8



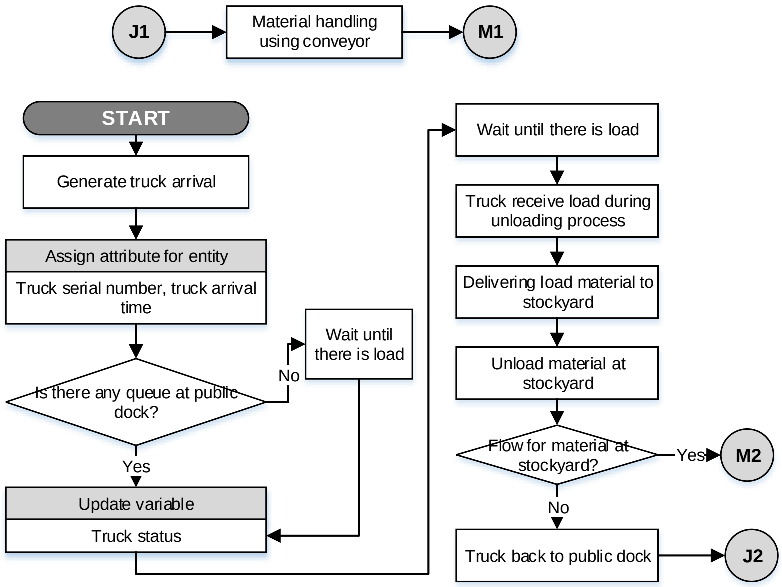

## APPENDIX 9: LOGIC FLOW OF SUB MODEL 9



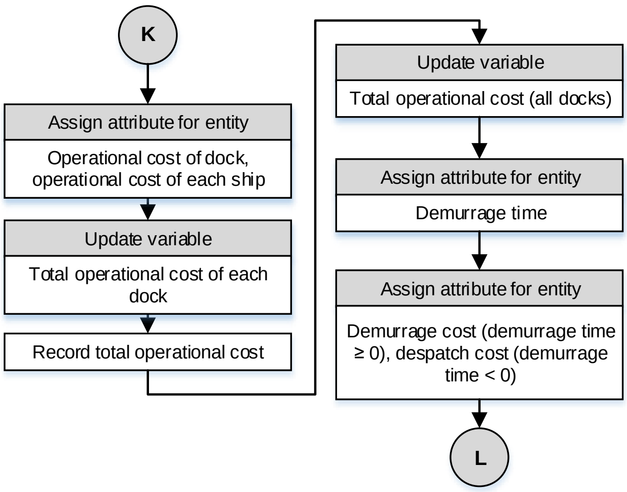
# APPENDIX 10: LOGIC FLOW OF SUB MODEL 10



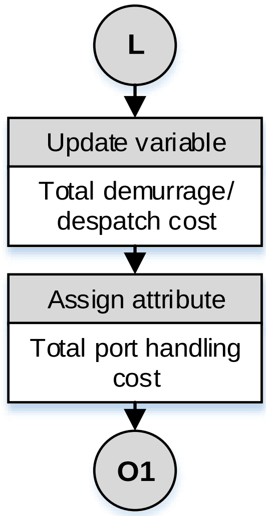

# APPENDIX 11: LOGIC FLOW OF SUB MODEL 11



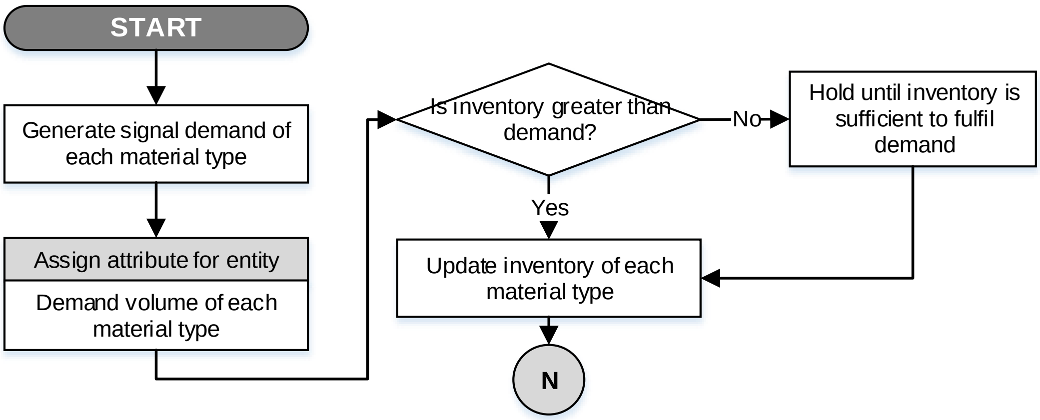

# APPENDIX 12: LOGIC FLOW OF SUB MODEL 12



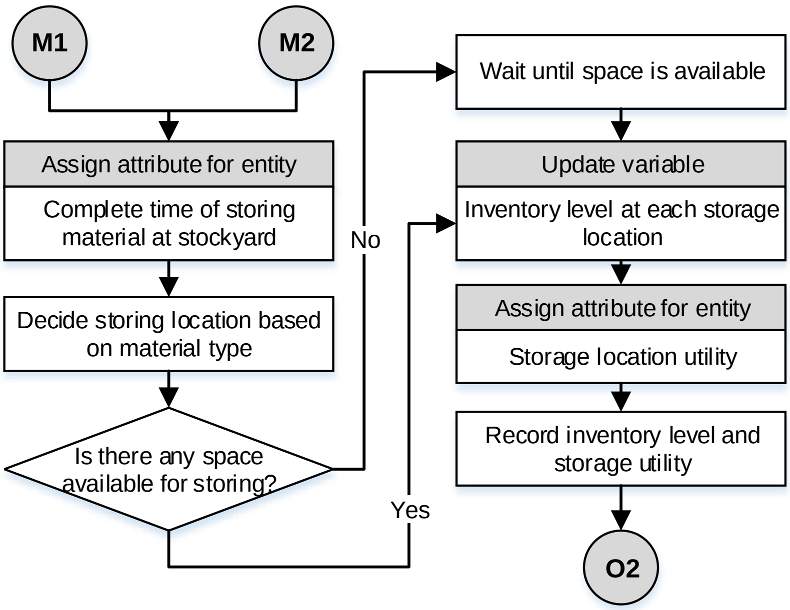
# APPENDIX 13: LOGIC FLOW OF SUB MODEL 13



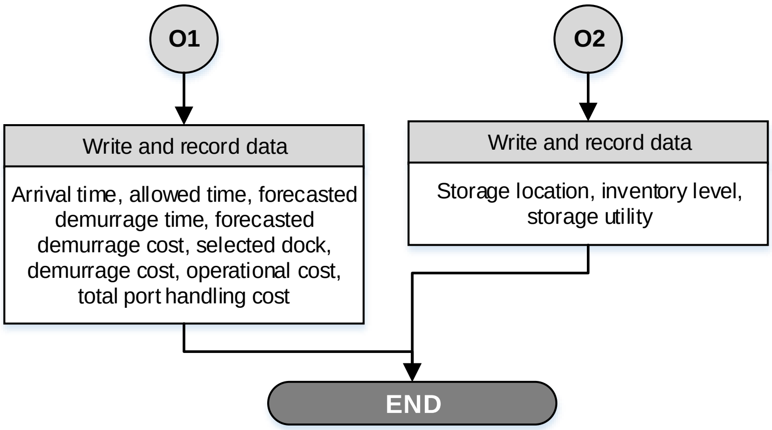

# APPENDIX 14: LOGIC FLOW OF SUB MODEL 14




# APPENDIX 15: LOGIC FLOW OF SUB MODEL 15



# APPENDIX 16: LOGIC FLOW OF SUB MODEL 16

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