Cargo Allocation Model by Mixed Integer Linear Programming Approach to Minimize Demurrage Ship Cost

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Abstract

All companies must have competitive advantages to survive in this globalization era. Nowadays, the company needs a good priorities and systems, work efficiently, on time, good quality and low costs. The coal mining industry is an industry that is still in great demand by investors because of Indonesia's large coal reserves and Indonesia's strategic location so that the business competition is very tight. In addition, Indonesia is the world's largest coal exporter in 2020 with export volume reaching 405 million tonnes. Ship loading schedule is a major activity that have big impact to company profit and loss such as quality of coal cargo, demurrage ship cost, commercial price and opportunity loss, it is also has impact for the customer satisfaction. This research aims to make cargo allocation optimization model to minimize demurrage ship cost by using mixed integer linear programming. Laytime stop are the decision variable needed to find and software Excel solver is a instrument used for this model. Constraints used for this model are total cargo allocation must be equal to capacity of vessel, cargo allocation per day must be equal or less than loading rate vessel per day, daily inventory is fully used and excess time must be equal or higher than 0. The results show that the demurrage cost decreased 16.47 % compared to manual method. Sensitivity analysis of ship capacity and inventory constraints mostly affects to demurrage cost about $ 0.38644 per 1 ton of increase in ship capacity or decrease in daily inventory.

Keywords
Cargo allocation, mixed integer linear programming, minimize, demurrage ship cost.

1. Introduction
The rapid development and competition of business require business actors must have a competitive advantage to survive. Nowadays, the company needs good priorities and systems, work efficiently, on time, good quality, and low costs. The coal mining industry is an industry that is still in great demand by investors because of Indonesia's large coal reserves and Indonesia's strategic location so the business competition is very tight.

Indonesia's coal reserves reach 38.84 billion tons. With an average coal production of 600 million tons per year, the lifetime of coal reserves is still 65 years if it is assumed that there are no new reserves found (ESDM, 2021).
From the demand side, low calorific value coal is main supply for power plants in Indonesia. Indonesia is the world's largest coal exporter in 2020 with export volume reaching 405 million tonnes

The process of determining coal loading scheduling priorities has many complex problems with many criteria factors such as weather and tidal condition, inventory, and distribution system. Optimal scheduling and loading of coal barges will shorten the duration of the barging cycle (cycle time) so that coal shipment is achieved, contract commitments with Buyers/Traders are maintained, customer satisfaction is achieved, avoiding lost opportunity barging activity and can avoid detention barges claims and demurrages vessels due to delay in coal loading. (S. Yusuf, 2021).

Table 1. Demurrage cost per metric tonnes PT “X” 2020-2022 (until September)

Year	**USD / MT**

2020	0.09
2021	1.55
2022 (until September)	0.03

The above table (Table 1) shows the demurrage cost (USD / MT) of PT “X” period 2020 until 2022 (September). PT “X” is one of the coal mining companies in Indonesia that produce low rank coal. Coal shipment scheduling at PT "X" usually uses the first come first serve method and there is no measurable mathematical model.

The urgency of this research is the ship's demurrage value which causes losses to the company so it needs to be reduced, in this research the optimization is carried out on the allocation of coal cargo (floating barge) which will be loaded into the vessel. There are only a few research that discusses the optimal allocation of cargo (floating barge) to minimize ship demurrage costs in the coal industry (dry bulk cargo). Previous studies generally discussed the shortest route in container shipping with optimal cargo allocation for minimizing transportation costs and for optimal scheduling of ship unloading in the steel industry (Gao et al. 2021). In terms of the variables used are also different, in this study using variable loading rate vessel and laytime.

1.1 Objectives
This research aims to make a cargo allocation optimization model to minimize demurrage ship costs by using mixed integer linear programming.

2. Literature Review
2.1 Scheduling
Having determined the sequence that work is to be tackled in, some operations require a detailed timetable showing at what time or date jobs should start and when they should end – this is scheduling. (Slack et al. 2013).

A good schedule has multiple criteria/ These criteria are as follows:
• Time for completion of all work (makespan), namely by measuring the total time required to complete all existing work. The smaller the makespan value indicates that the company's productivity is getting better.
• Average flow time, namely by calculating the average time needed to complete each job. The smaller average flow time value indicates that the company's productivity is getting better.
• Average lateness, namely by calculating the average difference between the actual completion time and the given due date. The smaller average lateness value indicates that the company's productivity is getting better.

2.2 Sequencing
Decisions must be taken on the order in which the work will be tackled. This activity is termed ‘sequencing’. (Slack et al. 2013).

Sequencing priority is divided into several types of considerations, namely:
• Due Date where jobs are prioritized according to when they are 'due' for delivery.
• Last in First Out (LIFO) where priority is based on the last order first.
• First in First Out (FIFO) where priority is based on the order in which they arrive to be served. Often called first-out sequencing (FIFO), or sometimes 'first come, first served' (FCFS).
• Longest Operation Time (LOT) where priority is based on the work that has been operating for the longest time or done first.
• Shortest Operation Time (SOT) where priority is based on the job with the fastest operation or processing it first.

2.3 Laytime and Demurrage
Laytime is ‘the period of time agreed between the parties during which the Owner will make and keep the vessel available for loading or discharging without payment additional to the freight’.

Consequently, when there are delays involved in loading and discharging the pre-agreed laytime allowed for loading and discharging can be exceeded. If this is the case, additional freight is due to the Owner. This additional freight is commonly known as 'demurrage'. Demurrage is 'an agreed amount payable to the Owner in respect of delay to the vessel beyond the laytime, for which the Owner is not responsible. Demurrage shall not be subject to laytime exceptions'. (Erwin de Zwarte, 2007)

2.4 Sales Scheme

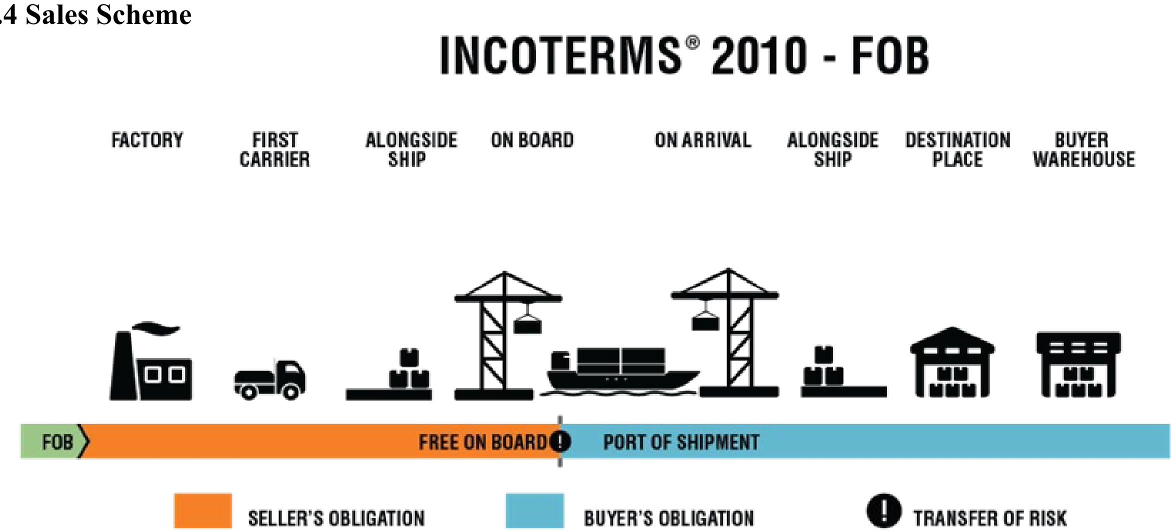

Figure 1. FOB Incoterms (Incoterms, 2010)

FOB (Free on board) Sales Scheme (Figure 1) is a scheme which can only be used for sea transportation, the seller's responsibility ends when the goods have been placed on board. In this study, the sales scheme is FOB Vessel, the researcher's position is as a seller (seller) so all responsibility, costs, and arrangements will be the responsibility of the seller until the goods are placed on the vessel. The allocation of cargo using floating barges for transshipment loading to vessels

2.5 Transshipment

The transshipment model is a transportation model that allows the indirect delivery of goods (commodities), where goods from one source can be at another source or destination before reaching their final destination (Dimyati, 2004).

2.6 Optimization and Linear Program

According to the Big Indonesian Dictionary KBBI (2008), that optimization comes from the word optimal which means the best, highest, or most profitable. Optimizing means making the best or the highest.

According to Siswanto (2007), a linear program is a model used to determine a decision variable that will maximize or minimize the objective function which is limited by several constraints. The linear program contains 3 basic elements namely

1. Decision variables

Variables to be searched for to give the best value for the goals to be achieved

2. Objective Function

In the form of a mathematical function that must be maximized or minimized which reflects the goals to be achieved

3. Constraint Function

In the form of a mathematical function that represents the constraints that exist in an attempt to maximize or minimize the objective function

The basic form of the Linear Method Program is as follows:

Objective Function

Maximize or minimize : $Z = C_1X_1 + C_2X_2 + ... + CnXn$

Constraint : $a_{11}X_1 + a_{12} X_2 +...+ a_{1n}X_n < b1$
$X_1 ,X_2,...,X_n > 0$

Z : objective function
C_j : parameter of objective value
X_j : decision variable
a_{ij} : coeficient
b_i : constanta

2.7 Simplex Method

According to Sitinjak (2006), the methods that can be used to find solutions to the linear program model are divided into 2, namely:
• Graphical Method Used when the number of decision variables in the linear programming model is two decision variables. (= 2 variables).
• Simple Method
Used when there are many decision variables in the linear programming model

2.8 Sensitivity Analysis

According to Taha (2017), In LP, the parameters (input data) of the model can change within certain limits without causing changes in the optimum. This is referred to as sensitivity analysis and divide into 4 categories :

1. Graphical Sensitivity Analysis
2. Algebraic Sensitivity Analysis – Changes in the Right-Hand Side
3. Algebraic Sensitivity Analysis – Objective Function
4. Sensitivity Analysis with TORA, solver, and AMPL

In the real world, constraints caused by limited resources often change easily, as well as prices of products, profit margins, production costs, etc. These changes will affect in changes in the mathematical model. There are several possible changes such as:

1. Changes in resource capacity (value of the right-hand side)
2. Price/profit changes (objective function coefficient)
3. Changes to the elements in the coefficient matrix
4. Changes in the number of variables
5. Changes in the number of inequalities/equations in the constraints.

(Suyitno, 2018)

3. Methods

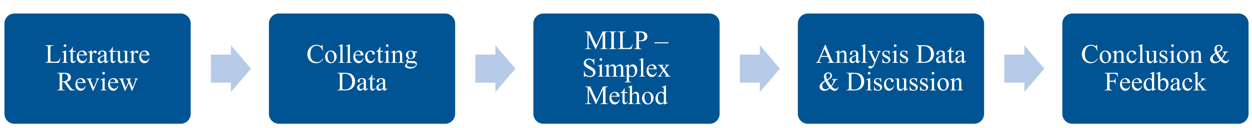

Figure 2. Flow chart method

The above figure showed the step by step for doing this research (Figure 2). The first step is the various kind of journals were explored and a research gap was found to get the novelty. We started to read literatures about scheduling, sequencing, laytime and demurrage.

The second step, we collected secondary data from PT "X" and input to Excel sheet. After that, the important data were picked and separated for data processing. We used Mixed Integer Linear Programming with Simplex Method and processed in the Excel Solver Program, the decision variable was laytime stop. Then, we tried to make objective function and constraints with mathematical notation. The objective function was minimized demurrage cost of the ship and constraints used for this model were total cargo allocation must be equal to the capacity of vessel, cargo allocation per day must be equal or less than the loading rate vessel per day, daily inventory was fully used, and excess time must be equal or higher than 0. After all the constraints, and objective functions had already been input into the Solver then we started to run the model.

The third step, after the result was coming out, we compared the result to the existing problem and calculated how much saving in dollar cost and percentage. We started to analyze and discuss the results.

The fourth step, the sensitivity analysis was conducted then make conclusions and feedback for future research.

MILP has the advantages of precision, flexibility, and extensive modeling capabilities to be one of the most widely explored methods for process scheduling problems (Christodoulos A. Floudas and Xiaoxia Lin, 2005). It was successfully applied to minimize total transportation costs and reduce demurrage costs by 20% for ship discharging in the steel industry (Gao et al. 2021).

4. Data Collection

The secondary data from PT "X" was collected. The data type were qualitative and quantitative data such as vessel capacity, type of vessel, demurrage rate per day, timesheet, and cargo inventory with total 9 vessels and 21 days of schedulling

The following are the nomenclature, objective function, constraints that have been made in mathematical notation:

Index :

i : Mother Vessel

t : time period

Set :

I : Mother Vessels

T : time period

Objective function :

$$\text{Min} \sum_{i \in I} Ci \ \ (t_i^s - T_i^d)$$

C_i : demurrage cost vessel i per day, $i \in I$

T_i^d: *due date laytime* vessel i, $i \in I$, $t \in T$

t_i^s : *laytime stop vessel* i, $i \in I$, $t \in T$

$$t_i^s = t_i^a + W_{it} + P_{it}$$

t_i^a: laytime start, $i \in I$

W_{it} : waiting time vessel i on time period t, $i \in I$, $t \in T$

P_{it} : effective loading time vessel i on time period t, $i \in I$, $t \in T$

P_{it} : V_i / L_{it}

V_i : volume capacity *vessel* i, $i \in I$

L_{it} : *loading rate* vessel i on time period t, $i \in I$, $t \in T$

Constraints :

1. Total cargo allocation equal to volume capacity vessel

$$\sum Hit \quad = \quad V_i$$

H_{it} : $cargo\ allocation\ vessel\ i\ on\ time\ period\ t$, $i \in I$, $t \in T$

V_i : volume capacity *vessel* i, $i \in I$

2. Total cargo allocation at vessel are lower or equal to the inventory

$$\sum H_{it} \leq \sum H_{t-1}$$

H_{it} : $cargo\ allocation\ vessel\ i\ on\ time\ period\ t$, $i \in I$, $t \in T$

H_{t-1} : $floating\ barge\ inventory\ on\ time\ period\ t$, $t \in T$

In this condition the total inventory is larger, 602,000 MT while the demand for loading cargo allocation is only 560,540 MT, using this constraint the daily inventory is not fully loaded and cargo allocation is not optimal so additional constraints are needed

$$\sum H_{i8\text{-}19} = \sum H_{8\text{-}19_{-1}}$$

Total cargo allocation on days 8-19 is equal to inventory on days 8 – 19 and total cargo allocation on the last day or days 20 is equal to 540 MT.

$$\sum H_{i20} = 540$$

3. Total cargo allocation per day is always lower than loading rate vessel per day

$$H_{it} \leq L_{it}$$

H_{it} : $cargo\ allocation\ vessel\ i\ on\ time\ period\ t$, $i \in I$, $t \in T$
L_{it} : $loading\ rate\ vessel\ i\ \ on\ time\ period\ t$, $i \in I$, $t \in T$

4. For the value $(t_i^s - T_i^d)$ is always positive or equal to zero, the additional constraint is needed

$$(t_i^s - T_i^d) = x$$
$$x \geq 0$$
$$x \leq \infty$$
$$x \leq (t_i^s - T_i^d) + M.\, w$$
$$w \in \{0,1\}$$

There are assumptions used in this study to make the model easier and to get closer to the real problem conditions, namely:

1. All ships can load cargo at the same time
2. Cargo delivery is assumed to use cargo on floating barges to be loaded onto ships per day at the anchorage point in the transshipment activity.
3. The loading rate in this model uses the actual loading rate of the loading vessel.

The next stage is the sensitivity analysis which is obtained when the model is running in the Excel Solver software.

5. Results and Discussion

5.1 Graphical Results

The Optimal Cargo allocation to each vessel is given in Table 2.

Table 2. Optimal Cargo allocation to each vessel

	Changing Variable											
Cargo Allocation (Hit)	MV. A	MV. B	MV. C	MV. D	MV. E	MV. F	MV. G	MV. H	MV. I	Inventory (Ht-1)		
Day-1	0	0	0	0	0	0	0	0	0	0	<=	0
Day-2	0	0	0	0	0	0	0	0	0	0	<=	0
Day-3	0	0	0	0	0	0	0	0	0	0	<=	0
Day-4	0	0	0	0	0	0	0	0	0	0	<=	0
Day-5	0	0	0	0	0	0	0	0	0	0	<=	0
Day-6	0	0	0	0	0	0	0	0	0	0	<=	0
Day-7	0	0	0	0	0	0	0	0	0	0	<=	0
Day-8	6,730	4,513	2,757	0	0	0	0	0	0	14,000	=	14,000
Day-9	11,714	9,301	0	3,945	0	10,040	0	0	0	35,000	=	35,000
Day-10	15,634	9,301	0	3,065	0	0	0	0	0	28,000	=	28,000
Day-11	15,634	9,083	14,981	13,278	0	3,024	0	0	0	56,000	=	56,000
Day-12	15,634	9,301	14,981	13,278	0	9,806	0	0	0	63,000	=	63,000
Day-13	1,592	9,301	14,981	13,278	15,526	10,040	5,282	0	0	70,000	=	70,000
Day-14	6,562	0	0	13,278	15,526	10,040	9,347	15,247	0	70,000	=	70,000
Day-15	0	0	0	13,278	12,941	0	0	1,273	7,508	35,000	=	35,000
Day-16	0	0	0	0	15,526	0	9,347	15,139	15,988	56,000	=	56,000
Day-17	0	0	0	0	8,418	0	9,347	15,247	15,988	49,000	=	49,000
Day-18	0	0	0	0	3,745	0	7,020	15,247	15,988	42,000	=	42,000
Day-19	0	0	0	0	1,418	0	9,347	15,247	15,988	42,000	=	42,000
Day-20	0	0	0	0	0	0	0	0	540	540	<=	28,000
Day-21	0	0	0	0	0	0	0	0	0	0	<=	14,000
Vessel Capacity (Vi)	73,500	50,800	47,700	73,400	73,100	42,950	49,690	77,400	72,000			
	=	=	=	=	=	=	=	=	=		Total Inventory	
	73,500	50,800	47,700	73,400	73,100	42,950	49,690	77,400	72,000		602,000	
Total Capacity Vessel	560,540											

Optimal cargo allocation become the basis for the next step in determining the laytime stop (Table 3).

Table 3. Laytime stop in days

Laytime Stop in days	
MV. A	13.42
MV. B	13.00
MV. C	13.00
MV. D	15.00
MV. E	18.09
MV. F	14.00
MV. G	18.03
MV. H	19.00
MV. I	20.00

Table 4. Comparison table existing demurrage cost and minimize demurrage cost

Total Demurrage ($)	*Existing*	Minimize
MV. A	-46,290.93	-53,587.45
MV. B	-28,451.54	-25,536.42
MV. C	-19,925.91	-15,391.63
MV. D	-12,280.40	-17,115.19
MV. E	-14,550.00	-19,933.98
MV. F	-33,202.32	-5,658.56
MV. G	-7,329.39	-6,353.46
MV. H	-26,509.15	-20,390.84
MV. I	-15,304.39	-6,301.81
Total	-203,844.03	-170,269.34
Saving	-33,574.69	
% Saving	16.47%	

Laytime stop is the decision variable needed to find in this model (Table 4). After we start running the model, the demurrage value result is $ 170,269.34, and when compared with the manual loading schedule there is a 16.47% reduction in demurrage costs (Table 5). In this model, there are 6 vessels namely MV. B, MV. C, MV. F, MV. G, MV. H and MV. I are minimized. In addition to minimizing demurrage costs, this model can indirectly increase customer satisfaction because the smaller the demurrage costs, the faster the vessel is loaded and arrived at the buyer's place. According to Inghilleri & Solomon (2010), customers will be satisfied if they consistently receive products that are delivered on time and there are no delays (in a timely fashion). When compared to previous research on ship unloading optimization of the steel industry, a savings of 20% in demurrage costs was achieved (Gao et al. 2021). In the refined oil shipping industry, optimal ship scheduling using MILP results is 6% saving in transportation costs (Yixin Ye et al. 2017). The MILP model that proposes both the optimization of the ship departure schedule and the cargo allocation scheme takes into account the waiting time and demurrage costs at the port (Wang et al. 2014).

The amount of inventory per day in both stockpile and floating barges, effective cargo allocation, capacity and condition of equipment for loading, availability of barges and floating cranes, weather conditions, number and expertise of manpower greatly affect the cost of demurrage vessels because they relate to the loading rate of ships per day and ship waiting time. For this reason, the company needs to ensure that the amount of inventory is sufficient to load the vessel within a certain period time, it is necessary to monitor the performance of the floating crane per day and ask the vendor to replace it with another floating crane or carry out periodic maintenance and if the vessel uses its own crane for loading or geared vessel it is necessary to ascertain the crane and grab specifications, then request a certificate or maintenance history from the vessel to maintain the achievement of the loading rate per day. Priority considerations for scheduling sequences refer to the due date of work (Slack et al. 2013). In this model is due date laytime,

Table 5. Sensitivity analysis of w value

Variable Cells

Cell	Name	Final Value	Reduced Cost	Objective Coefficient	Allowable Increase	Allowable Decrease
B117	0/1 MV. A	0	0	0	1E+30	0
C117	0/1 MV. B	0	0	0	1E+30	0
D117	0/1 MV. C	0	0	0	1E+30	0
E117	0/1 MV. D	0	0	0	1E+30	0
F117	0/1 MV. E	0	0	0	1E+30	0
G117	0/1 MV. F	0	0	0	1E+30	0
H117	0/1 MV. G	0	0	0	1E+30	0
I117	0/1 MV. H	0	0	0	1E+30	0
J117	0/1 MV. I	0	0	0	1E+30	0

The value of w as a changing variable can only be increased by 1E+30 or infinity but still does not affect the final value of 0 (Table 6).

Table 6. Sensitivity Analysis Table Constraint Capacity Vessel

Constraints

Cell	Name	Final Value	Shadow Price	Constraint R.H. Side	Allowable Increase	Allowable Decrease
B222	Vessel Capacity (Vi) MV. A	73500	0.38644854	73500	2327	0
C222	Vessel Capacity (Vi) MV. B	50800	0.38644854	50800	2327	0
D222	Vessel Capacity (Vi) MV. C	47700	0.38644854	47700	2327	0
E222	Vessel Capacity (Vi) MV. D	73400	0.38644854	73400	2327	0
F222	Vessel Capacity (Vi) MV. E	73100	0.38644854	73100	14000	0
G222	Vessel Capacity (Vi) MV. F	42950	0.38644854	42950	2327	0
H222	Vessel Capacity (Vi) MV. G	49690	0.38644854	49690	2327	0
I222	Vessel Capacity (Vi) MV. H	77400	0.38644854	77400	12941	0
J222	Vessel Capacity (Vi) MV. I	72000	0.38644854	72000	8480	0

The variable vessel capacity constraint will affect the increase in demurrage costs of $ 0.38644 for every 1 ton increase in vessel capacity with a maximum increase of up to 2.327 MT for MV. A, MV. B, MV. C, MV. D, MV. F, MV. G while for the MV. E with a maximum increase by 14,000 MT, MV. H with a maximum increase by 12.941 MT and MV. I with a maximum increase by 8,480 MT (Table 7).

Table 7. Sensitivity Analysis Table Constraint Inventory Day 1-21

Cell	Name	Final Value	Shadow Price	Constraint R.H. Side	Allowable Increase	Allowable Decrease
K200	Day-1 Inventory (Ht-1)	0	0	0	0	0
K201	Day-2 Inventory (Ht-1)	0	-0.3864485	0	0	0
K202	Day-3 Inventory (Ht-1)	0	-0.3864485	0	0	0
K203	Day-4 Inventory (Ht-1)	0	-0.3864485	0	0	0
K204	Day-5 Inventory (Ht-1)	0	-0.3864485	0	0	0
K205	Day-6 Inventory (Ht-1)	0	-0.3864485	0	0	0
K206	Day-7 Inventory (Ht-1)	0	-0.3864485	0	0	0
K207	Day-8 Inventory (Ht-1)	14000	0	14000	1E+30	0
K208	Day-9 Inventory (Ht-1)	35000	0	35000	1E+30	0
K209	Day-10 Inventory (Ht-1)	28000	0	28000	1E+30	0
K210	Day-11 Inventory (Ht-1)	56000	0	56000	1E+30	0
K211	Day-12 Inventory (Ht-1)	63000	0	63000	1E+30	0
K212	Day-13 Inventory (Ht-1)	70000	0	70000	1E+30	0
K213	Day-14 Inventory (Ht-1)	70000	0	70000	1E+30	0
K214	Day-15 Inventory (Ht-1)	35000	0	35000	1E+30	0
K215	Day-16 Inventory (Ht-1)	56000	0	56000	1E+30	0
K216	Day-17 Inventory (Ht-1)	49000	0	49000	1E+30	0
K217	Day-18 Inventory (Ht-1)	42000	0	42000	1E+30	0
K218	Day-19 Inventory (Ht-1)	42000	0	42000	1E+30	0
K219	Day-20 Inventory (Ht-1)	540	0	28000	1E+30	27460
K220	Day-21 Inventory (Ht-1)	0	0	14000	1E+30	14000

Table 8. Sensitivity Analysis Table Constraint Inventory Day 8-20

Cell	Name	Final Value	Shadow Price	Constraint R.H. Side	Allowable Increase	Allowable Decrease
K207	Day-8 Inventory (Ht-1)	14000	-0.386448538	14000	0	2327
K208	Day-9 Inventory (Ht-1)	35000	-0.386448538	35000	0	2327
K209	Day-10 Inventory (Ht-1)	28000	-0.386448538	28000	0	2327
K210	Day-11 Inventory (Ht-1)	56000	-0.386448538	56000	0	2327
K211	Day-12 Inventory (Ht-1)	63000	-0.386448538	63000	0	2327
K212	Day-13 Inventory (Ht-1)	70000	-0.386448538	70000	0	2327
K213	Day-14 Inventory (Ht-1)	70000	0.069368911	70000	0	2327
K214	Day-15 Inventory (Ht-1)	35000	-0.386448538	35000	0	12941
K215	Day-16 Inventory (Ht-1)	56000	-0.386448538	56000	0	12941
K216	Day-17 Inventory (Ht-1)	49000	-0.386448538	49000	0	8418
K217	Day-18 Inventory (Ht-1)	42000	-0.386448538	42000	0	3745
K218	Day-19 Inventory (Ht-1)	42000	0	42000	0	1418
K219	Day-20 Inventory (Ht-1)	540	-0.386448538	540	0	540

Where the cargo allocation is smaller than the inventory for days 1-21, it can be seen that the inventory for days 1-7 (Table 8), the allowable increase and decrease in inventory value is 0 so it does not have any effect,
while the inventory for days 8-21, allowable increase in supply value is 1E+30 or infinity and decrease in inventory for day 8-19 is 0, day 20 is 27,460 MT and day 21 is 14,000 MT. However, it does not have any effect on demurrage costs because the shadow price value is 0

In the cargo allocation constraint on day 8 to day 20 or the last day the inventory must run out. Every decrease of 1 ton of inventory will affect reducing demurrage costs by $ -0.38644 on inventory days 8-13, 15-18, and day 20. On day 14, a decrease in inventory of 1 ton will give an increase in demurrage costs of $ 0.069 and inventory for day 19 does not affect on demurrage costs. Shadow prices are affected by a decrease in supply/allowable decrease.

The sensitivity analysis that has been carried out on vessel capacity and inventory constraints mostly has an effect of $ 0.38644 on the demurrage cost for every increase or decrease of 1 ton of coal. Vessel capacity will have an affect on increasing costs if it is increased according to the allowable increase and inventory will have an effect if it is reduced according to the allowable decrease

5.2 Proposed Improvements

The model in this research still has limitations because using the Excel Solver solver is only limited to 200 cells while changing variable cargo allocation in this research are 189 cells, so the scheduling with many vessels over a long period time cannot be done in the same worksheet. This model can still be developed into a broader transshipment model with more complete data such as the number of barges available, cost, distance, and transshipment time from barge to vessel.

6. Conclusion

There is an efficiency with value $ 33,574.69 or 16.47% demurrage costs from the model. This model minimizes 6 out of 9 ships, namely MV. B, MV.C , MV. F, MV. G, MV. H and MV. I which indirectly improves customer satisfaction due to reduced delays because the ship finishes loading faster. Sensitivity analysis on changes in constraint values gives an effect if the vessel capacity is increased and the amount of inventory is decreased with most of the values that appear are $ 0.38644. This model is more scalable and efficient than the manual scheduling method.

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