The Asian Journal of Shipping and Logistics 37 (2021) 220–230

HOSTED BY

ELSEVIER

Contents lists available at ScienceDirect

The Asian Journal of Shipping and Logistics

journal homepage: www.elsevier.com/locate/ajsl

Multi-objective optimization of petroleum product logistics in Eastern Indonesia region

Farhan Surury[a,b], Ahmad Syauqi[a,b], Widodo Wahyu Purwanto[a,b,*]

[a] Sustainable Energy Systems and Policy Research Cluster, Universitas Indonesia, Depok 16424, Indonesia
[b] Chemical Engineering Department, Faculty of Engineering, Universitas Indonesia, Depok 16424, Indonesia

ARTICLE INFO

Article history:
Received in revised form 6 May 2021
Accepted 29 May 2021

Keywords:
Green logistic
Petroleum product
Optimization
Transportation cost
GHG emissions

ABSTRACT

The transportation sector is one of the largest fuel consumers and pollutant contributors worldwide. The International Maritime Organization predicts that the greenhouse gas (GHG) emissions from transportation will be increasing significantly until 2050, driven by the growth in global maritime trade. Managing logistics distribution routes is considered a possible approach for controlling GHG emissions. This study aims to implement a green logistics concept in the logistics distribution of petroleum products—gasoline, kerosene, and diesel—in eastern Indonesia, whose supply sources are refineries located in Balikpapan and Kasim. A multi-objective approach is used to implement the green logistics concept. Multi-objective optimization is conducted using the AIMMS software to optimize a logistics system consisting of a multi-depot, multi-product, and heterogeneous fleet. The optimization is performed to determine the best logistics route and the amount of products delivered using certain types of fleets to minimize transportation cost and GHG emissions using constant speed. In addition, this study also investigates the effect of variable speed on cost and CO_2 emissions. For the constant speed case, the distribution routes obtained for the minimizing cost scenario tends to maximize the utilization of transit terminals while in the minimizing emissions scenario tends to deliver directly to the distribution centers, so the route decision in multi-objective optimization scenario is combination of the two. The multi-objective optimization results an 11% cost reduction and a 17% GHG emission reduction compared with the current values. The comparison between constant and variable speed reveals that the variable speed is preferred to constant speed as it gives lower emissions with slight changes in cost.

1. Introduction

Marine transportation is an essential part of the logistics system and is the fundamental infrastructure for supporting economic growth. However, the marine transportation sector is one of the largest fuel consumers and contributes to most of the pollution worldwide. In 2014, the International Maritime Organization (IMO) conducted a third study on greenhouse gases (GHGs), estimating that international transport activities produced 796 million tons of CO_2 or approximately 2.2% of the total global anthropogenic CO_2 emissions in 2012. Moreover, it was predicted that emissions from these activities could increase by 50–250% by 2050, primarily owing to the growth of global maritime trade. The Marine Environmental Protection Committee of the IMO has considered controlling GHG emissions from ships. In 2011, it presented a technical package for new vessels and operational emissions reduction for all vessels in Chapter 4 of MARPOL Annex VI entitled, “Energy efficiency regulations for ships.” As per the regulations, one of the main steps is to establish mechanisms for ship owners to improve the energy efficiency of both new and existing vessels through route optimization, trim and draft optimization, speed optimization, and on-time arrival at ports (IMO, 2019).

Indonesia is a country that depends on marine business because it consists of many islands. The distribution of petroleum products, which are essential commodities in Indonesia, relies on sea transportation. More than 80% of the petroleum product distribution activities in Indonesia use marine fleets, particularly in eastern Indonesia. Eastern Indonesia, including Kalimantan, Sulawesi, Maluku, and Papua, is mainly supplied by the Balikpapan and Kasim refinery units. An Indonesian downstream oil and gas regulatory body called BPH Migas categorizes this distribution area as commercial distribution region (CDR) III (DRAOG, 2019).

According to Psaraftis (2016), one of the fundamental approaches for reducing maritime emissions (GHG and others) is

* Corresponding author.
E-mail address: widodo@che.ui.ac.id (W.W. Purwanto).

https://doi.org/10.1016/j.ajsl.2021.05.003

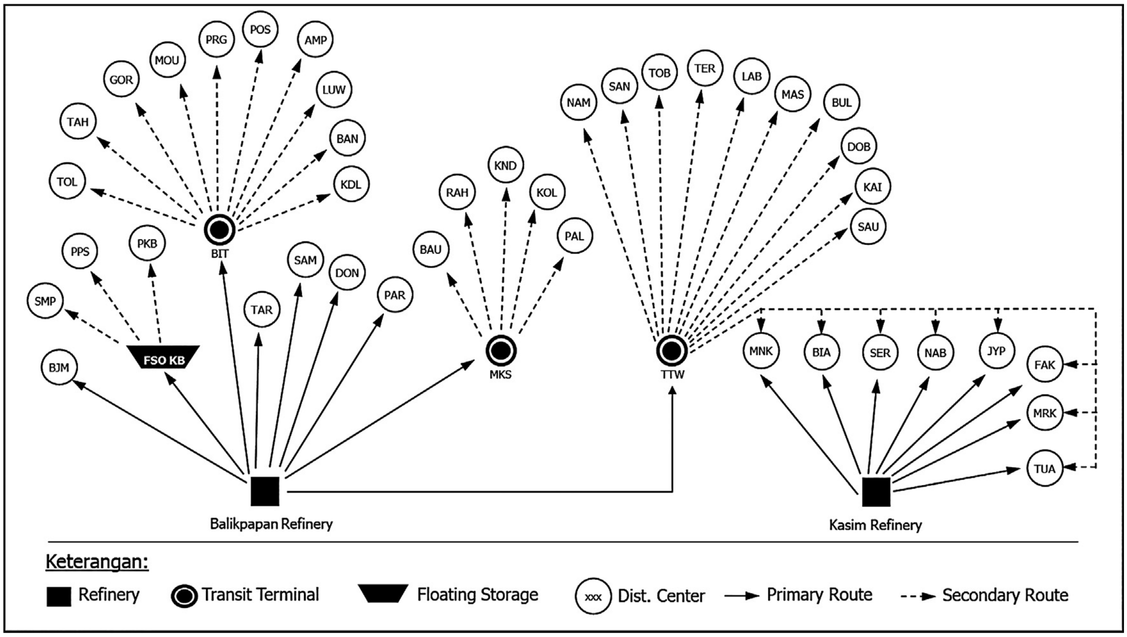

Fig. 1. Petroleum Products Supply Chain Network.

tactical logistics operation based on routing optimization; however, it may have an economic impact. Green logistics is a concept related to the sustainable production and distribution of goods, considering environmental and social factors. Therefore, the objective is not only associated with the economic impact of the logistics of an organization but also with the broader implications for society, such as the environmental impact of pollution. The scope of green logistics activities includes measuring the environmental impact of different distribution strategies, reducing energy use in logistics activities, reducing waste, and managing waste processing (Sbihi & Eglese, 2007). According to Psaraftis and Kontovas (2009), optimal fleet management can lower the intensity of CO_2 emission per kiloliter-kilometer. Many researchers have recently conducted route optimization to determine the importance of applying vehicle routing problems (VRPs) to consider environmental aspects, such as reducing CO_2 emissions, and the results have been found to be closely related to fuel consumption (Kramer et al., 2015). Bektaş and Laporte (2011) first introduced a VRP model considering environmental aspects; the model, known as the pollution routing problem, was subsequently developed by Demir et al. (2012) using a more accurate fuel consumption function.

Some researchers have considered emissions factors by implementing multi-objective optimization (MOO), which optimizes vehicle routes by reducing fuel consumption, *e.g.*, Kuo and Wang (2011) and Eshtehadi et al. (2017). In their study, (Jabali, Van Woensel, & de Kok, 2012) considered a trade-off between CO_2 emissions and travel time in a VRP with time dependencies, and Rabbani et al. (2018) implemented a VRP by accommodating multi compartments. However, the scope of the aforementioned studies covered land vehicle cases and non-petroleum sectors. Wang et al. (2018) studied the optimization of refinery product distribution and its counterbalance for carbon emission reduction by considering carbon tax factors that significantly contribute to emission reduction from maritime transportation in a single-depot system.

Although in recent years, there have been numerous studies on VRPs considering emission factors (also known as green VRPs (GVRPs)), few studies have focused on MOO of petroleum product logistics considering economic and environmental aspects with multi-depot systems, various products, and heterogeneous ship transportation. Thus, we believe that the novelty of this research is the application of this approach.

This study aims to apply the green logistics concept through MOO of the transportation costs and CO_2 emissions of multi-depot systems with heterogeneous ship transportation. A case of logistics distribution of gasoline, kerosene, and diesel products in CDR III supplied by refineries in Balikpapan and Kasim is considered.

2. Methodology

2.1. Problem definition

The distribution network (Fig. 1) consists of three nodes: refinery (N_0), transit terminal (N_S), and distribution center nodes (N_C). Petroleum fuel distribution activities in eastern Indonesia utilize two types of tankers: general-purpose (GP) and medium-range (MR) class tankers (whose characteristics are listed in Table 1). Products are delivered from the Balikpapan and Kasim refineries to fulfill the demands of the distribution centers. Some products are delivered directly to the distribution centers by MR tankers and the others by GP tankers, depending on the demand volume. Transit terminals are utilized as buffer supplies to satisfy the demands of Kalimantan, Sulawesi, and Maluku (Pertamina, 2018).

The product distribution from the Balikpapan refinery uses eight MR types, and the distribution network is integrated with the Kotabaru floating storage and Offloading (FSO KB) and the transit terminals in Bitung (BIT), Makassar (MKS), and Wayame (TTW). The distribution of the products from the Kasim refinery uses two GP-type vessels to meet the demand of Papua. The demand of each distribution center is listed in Table 1.

The distances, tanker sizes, and tanker speeds listed in Table 2. The distances between the refineries, transit terminals, and distribution centers were estimated using an application available on Shiptraffic.net (2020), based on the coordinates of each location (see Appendix A). Chartering is one of the options for providing transportation fleets in the logistics industry. The fare may be specified as per-ton on a particular route or as the total cost (generally in USD) per day for the duration agreed in the contract (Rai, 2013). The charter rate strongly depends on the size of the ship used and the rental time. Referring to the November 2019 prediction by Hellenic Shipping (2019) and assuming that the tankers are chartered for five years, the charter rates of the GP and MR types are also listed

Table 1
Product Demand.

Number	Refinery/Transit Terminal/Distribution Center	Abbreviation	Location	Gasoline (kL)	Kerosene (kL)	Diesel (kL)
1	Balikpapan refinery	BPP	Kalimantan			
2	Kasim refinery	KSM	Papua			
3	Kotabaru (FSO)	FKB	Kalimantan			
4	Bitung Terminal	BIT	Sulawesi			
5	Makassar Terminal	MKS	Sulawesi			
6	Wayame Terminal	TTW	Maluku			
7	Banjarmasin	BJM	Kalimantan	8,600		23,713
8	Sampit	SMP	Kalimantan	1,667		9,333
9	Pulang Pisau	PPS	Kalimantan	1,833	367	2,333
10	Kotawaringin	PKB	Kalimantan	2,400		8,133
11	Samarinda	SAM	Kalimantan	11,367		25,013
12	Tarakan	TAR	Kalimantan	4,133		17,647
13	Donggala	DON	Sulawesi	2,800		4,900
14	Pare-pare	PAR	Sulawesi	2,767		8,067
15	Bau-Bau	BAU	Sulawesi	2,600	1,333	4,333
16	Palopo	PAL	Sulawesi	1,733		3,300
17	Kolaka	KOL	Sulawesi	1,667		2,667
18	Raha	RAH	Sulawesi	1,500		1,500
19	Kendari	KND	Sulawesi	3,400		7,033
20	Tolitoli	TOL	Sulawesi	2,000		2,467
21	Tahuna	TAH	Sulawesi	600	400	767
22	Gorontalo	GOR	Sulawesi	1,967		1,400
23	Moutong	MOU	Sulawesi	933		1,033
24	Parigi	PRG	Sulawesi	1,333		5,000
25	Poso	POS	Sulawesi	1,217		1,617
26	Ampana	AMP	Sulawesi	1,500		5,000
27	Luwuk	LUW	Sulawesi	1,333		1,500
28	Banggai	BAN	Sulawesi	500	250	467
29	Kolonedale	KDL	Sulawesi	1,067		1,500
30	Namlea	NAM	Maluku	600	367	1,200
31	Sanana	SAN	Maluku	500	350	650
32	Labuha	LAB	Maluku	483	433	750
33	Ternate	TER	Maluku	1,400	1,950	5,500
34	Tobelo	TOB	Maluku	1,017	700	2,667
35	Masohi	MAS	Maluku	783	750	1,000
36	Bula	BUL	Maluku	400	350	833
37	Saumlaki	SAU	Maluku	400	550	900
38	Dobo	DOB	Maluku	367	367	1,800
39	Kaimana	KAI	Maluku	533	233	817
40	Tual	TUL	Maluku	1,833	767	6,633
41	Fakfak	FAK	Papua	633	283	550
42	Merauke	MKE	Papua	2,300	1,050	5,267
43	Manokwari	MNK	Papua	1,067		1,700
44	Biak	BIA	Papua	9,733	333	19,200
45	Serui	SER	Papua	550	283	767
46	Nabire	NAB	Papua	1,000		1,967
47	Jayapura	JYP	Papua	2,467	1,783	8,400

Table 2
Oil Tanker Characteristics and Charter Rate (Shiptraffic.net 2020).

Characteristic	Unit	General-Purpose (Handy)	Medium-Range (MR)
Size	DWT	18,000	32,000
	GT	13,500	21,900
Charter Rate (Hellenic Shipping, 2019)	$/per day pro-rated	14,250	15,000

in Table 2. Thus, the transportation cost can be determined based on the fuel consumption, charter rate, and fuel cost. The reader is recommended to refer to Ship and Bunker (2020) published February 2020, IFO 180 cSt price at 334 US$/MTon.

The assumptions used to perform the optimization are as follows: (a) the tankers are heterogeneous, (b) the tankers only park at the departing node, (c) each tanker returns to the departing node, (d) each tanker is loaded only at the departing node, (e) the customer demand is satisfied by one vehicle visit, (f) the transportation cost is proportional to the travel time, (g) the tanker speed is constant, (h) the tanker capacity is limited, and (i) each tanker is chartered for five years.

2.2. Mathematical model

The optimization model has two objective functions, Z_1 and Z_2, which are related to the minimization of the transportation cost (Eq. (1)) and CO_2 emissions (Eq. (4)). The abbreviation in the model is provided in Table 3.

$$\min Z_1 = \sum_k \sum_{(i,j)\in N} \boldsymbol{FC_{ijk}} \times \boldsymbol{t_{i,j,k}} \times \boldsymbol{Price_{MFO}} \times \boldsymbol{x_{ijk}} + \sum_k \sum_{(i,j)\in N} \boldsymbol{CC_{ijk}} \times \boldsymbol{t_{i,j,k}} \times \boldsymbol{x_{ijk}} \quad (1)$$

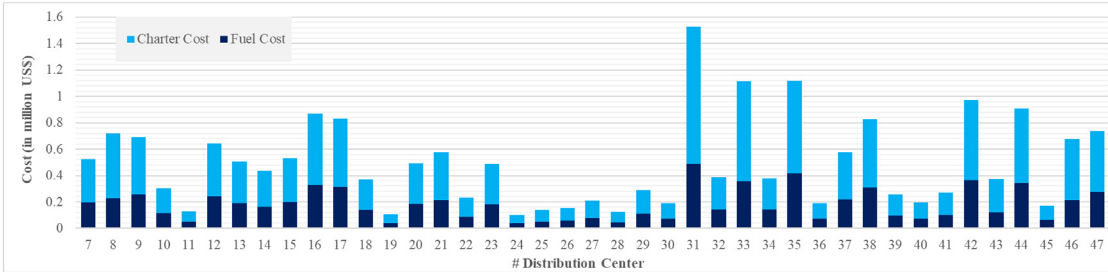

Fig. 2. Transportation Cost per Destination in Z_1 Minimization Scenario.

Table 3
List of Abbreviation.

Sets	
c	Customer nodes
d	Depot nodes
i	Origin nodes
j	Destination nodes
k	Type of ships
Objective Function & Constraint	
Z1	Objective Function 1 (minimize cost)
Z2	Objective Function 2 (minimize CO2eq emissions)
FC	Fuel consumption
x	Route decision variable
V	Ship's capacity
$Price_{MFO}$	Fuel price
LCU	Ship's load
CC	Daily ship's charter cost
Q	Transferred product
E	CO_{2eq} emissions
t	Cruising time
F	Emission factor
L	Distance
u	Ship's speed
D	Demand
Multi criteria decision making	
w	Weight
v	Normalized objective function matrix
S_+	Euclidean distance of each solution to the positive-ideal solution point
S-	Euclidean distance of each solution to the negative-ideal solution point
A-	Negative ideal solution
A+	Positive ideal solution
C	Closeness coefficient

Where

$$FC_{i,j,k} = (-40.0664 + 5.1367 \times u_{i,j,k})(0.5574 + 0.4426 \times LCU_{i,j,k}) \times 0.8 \quad (2)$$

$$t_{i,j,k} = \frac{L_{i,j}}{u_{i,j,k}} \quad (3)$$

$$\min Z_2 = \sum_k \sum_{(i,j)\in N} x_{ijk} \times E_{i,j,k} \quad (4)$$

Where

$$E_{i,j,k} = FC_{i,j,k} \times t_{i,j,k} \times F \quad (5)$$

As previously mentioned, there are two objectives in this study. The first objective is the minimization of the total cost which is defined by Eq. (1). The total cost includes two terms *i.e.,* fuel cost and charter cost. The first term is the fuel cost which is calculated by computing fuel consumption as a function of the ship's speed and load (Eq. (2)). The equations used to calculate fuel consumption are retrieved from (Bialystocki & Konovessis, 2016; Network for Transport Measures, 2021) for ships in the range of 10,000–60,000 DWT. The second term is the total charter cost which proportional to cruising time and daily charter cost. The second objective is CO_2 emissions (Eq. 4 taken from Hickman et al., 1999), the emission that is accounted only the direct emissions from logistic activities.

Both objectives are conflicting in terms that if one objective is to be minimized then the other will be maximized, hence MOO needs to be performed to select the optimal point from these conflicting objectives. the ε-constraint method is selected to perform MOO due to its simplicity, able to depict the whole non-dominated solution in a feasible region, and does not need weighting (Mavrotas, 2009). the ε-constraint method is performed by optimizing one objective and make the other as a constraint with the value of ε. The process is repeated with different values of ε until the Pareto frontier is formed (Lotov & Miettinen, 2008). Subsequently, the optimal point from a set of optimal point in the Pareto frontier is chosen using the TOPSIS method which is carried out based on the concept that the chosen point is the one that is closest to the positive ideal solution (*i.e.* the combination points of the best value from both objectives) and farthest to the negative ideal solution (*i.e.* the combination point of the worst value from both of the objectives). Based on Wang and Rangaiah (2017), the algorithm to conduct TOPSIS is as follows:

1 Construct normalized objective matrix with *x* rows and *y* columns by applying Eq. 6

$$Z_{x,y} = \frac{z_{x,y}}{\sqrt{\sum_{x=1}^{m} z_{x,y}^2}} \quad (6)$$

2 Construct weighted normalized objective matrix using Eq. 7

$$v_{x,y} = Z_{x,y} \times w_y \quad (7)$$

3 Determine the positive and negative ideal solution, A^+ and *A*-, for this case the positive ideal solution is the point constructed with minimal value of transportation cost and CO_2 emission, while the negative ideal solution is a point constructed with maximum value of transportation and CO_2 emissions.
4 Calculate the Euclidean distance between each point to positive and negative ideal solution by applying Eqs. 8 and 9

$$S_+ = \sqrt{\sum_{y=1}^{n} \left(v_{x,y} - A^+\right)^2} \quad (8)$$

$$S_- = \sqrt{\sum_{y=1}^{n} \left(v_{x,y} - A^-\right)^2} \quad (9)$$

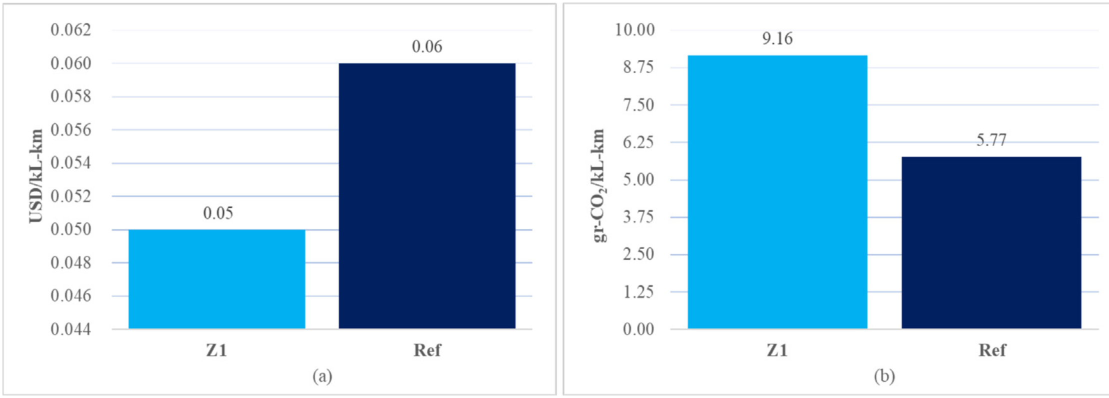

Fig. 3. Intensity of Cost per kL-km (a) and CO_2 per kL-km (b) in Z_1 Minimization Scenario.

Table 4
Distribution Routes in Z_1 Minimization Scenario.

Ship	Route	Ship	Route
MR 1	1 → 3 → 14 → 6 → 1	MR 5	5 → 16 → 17 → 18 → 15 → 5
MR 2	1 → 5 → 1	MR 6	6 → 32 → 33 → 31 → 29 → 19 → 18 → 30 → 6
MR 2	1 → 11 → 12 → 13 → 1	MR 7	3 → 7 → 3 → 7 → 9 → 3 → 8 → 10 → 3
MR 3	1 → 20 → 21 → 34 → 44 → 1	MR 8	4 → 22 → 23 → 24→ 25 → 26 → 27 → 28 → 4
MR 3	1 → 5 → 6 → 1	GP 1	2 → 40 → 39 → 41 → 36 → 2
MR 4	6 → 35 → 37 → 42 → 38 → 40 → 6	GP 2	2 → 43 → 45 → 46 → 47 → 2

Calculate the closeness coefficient using Eq. 10 The solution with largest closeness coefficient is then selected and called trade-off point.

$$\boldsymbol{C} = \frac{\boldsymbol{S}_-}{\boldsymbol{S}_- + \boldsymbol{S}_+} \tag{10}$$

The objective functions defined in Eqs. (1 and 4 are subjected to the constraint defined in Eqs. 11–19. Eqs. 11 and 12 is a constraint to ensure that only one destination can be chosen by one ship at one time. Eq. 13 limits the transferred cargo to never more than the ship's capacity. Eq. 14 is related to the volume balance *i.e.* the remaining cargo of a ship leaving a node will be considered in the next visit. Eq. 15 ensures that there is transferred cargo in every trip from nodes *i* to *j*. Eq. 16 shows that a ship can return to the original depot only when the cargo is empty. Eq. 17 limits the visit frequency, whereby any ship that leaves node *i* can only visit the other *j* nodes at most once. Eq. 18 warrants that the ships leaving the original depot return to the same depot. The optimization is performed using AIMMS version 4.79 with the CPLEX 20.1 solver (Bisschop, 2006). This model aims to determine the optimal total quantity of products transported from node *i* and *j* ($Q_{i,j,k}$) and the route of the ships. This paper assumes the speed of the ship is constant at 12 knots presented in section 3.1. this assumption is made to simplify the model and reduce computational time. However based on Psaraftis and Kontovas (2013), varying speed has significant effect on fuel consumption which effect cost and emission, hence this paper also study the effect of variable speed to cost and CO_2 emissions and compared it to the constant speed cases and presented in section 3.2.

$$\sum_{\boldsymbol{k}} \sum_{\boldsymbol{j} \in \boldsymbol{N}} \boldsymbol{x_{ijk}} = 1\,;\forall_{\boldsymbol{i}} \;\in\; (\boldsymbol{N}_0 \cup \boldsymbol{N})\,;\,\forall_{\boldsymbol{k}} \;\in\; \boldsymbol{K} \tag{11}$$

$$\sum_{\boldsymbol{k}} \sum_{\boldsymbol{i} \in \boldsymbol{N}} \boldsymbol{x_{ijk}} = 1\,;\forall_{\boldsymbol{j}} \;\in \boldsymbol{N}\,;\,\forall_{\boldsymbol{k}} \;\in\; \boldsymbol{K} \tag{12}$$

$$\boldsymbol{Q_{ijk}} \le \boldsymbol{x_{ijk}} \times \boldsymbol{V_k}\,;\,\forall(\boldsymbol{i},\boldsymbol{j}) \;\in\; \boldsymbol{A} \tag{13}$$

$$\sum_{\boldsymbol{k}} \sum_{\boldsymbol{i} \in \boldsymbol{N}} \boldsymbol{Q_{ick}} = \boldsymbol{D_j} + \sum_{\boldsymbol{k}} \sum_{\boldsymbol{j} \in \boldsymbol{N}} \boldsymbol{Q_{cjk}};\,\forall_{\boldsymbol{k}} \;\in \boldsymbol{K}\,;\,\forall_{\boldsymbol{c}} \;\in\; (\boldsymbol{N_c} \cup \boldsymbol{N}) \tag{14}$$

$$\boldsymbol{Q_{ij}} \ge 0;\forall(\boldsymbol{i},\boldsymbol{j}) \in \boldsymbol{A} \tag{15}$$

$$\sum_{\boldsymbol{k}} \sum_{\boldsymbol{i} \in \boldsymbol{N}} \boldsymbol{Q_{idk}} = 0\,;\,\forall_{\boldsymbol{d}} \;\in\; (\boldsymbol{N}_0 \cup \boldsymbol{N})\,;\,\forall_{\boldsymbol{k}} \in \boldsymbol{K} \tag{16}$$

$$\sum_{\boldsymbol{k}} \sum_{\boldsymbol{c} \in \boldsymbol{N_c}} \boldsymbol{x_{ick}} \le 1\,;\,\forall_{\boldsymbol{k}} \;\in \boldsymbol{K}\,;\,\forall_{\boldsymbol{c}} \;\in\; (\boldsymbol{N_c} \cup \boldsymbol{N}) \tag{17}$$

$$\sum_{\boldsymbol{j} \in \boldsymbol{N}} \boldsymbol{x_{ijk}} = \sum_{\boldsymbol{j} \in \boldsymbol{N}} \boldsymbol{x_{jik}};\,\forall_{\boldsymbol{k}} \;\in \boldsymbol{K}\,;\,\forall_{\boldsymbol{i}} \;\in\; (\boldsymbol{N}_0 \cup \boldsymbol{N}) \tag{18}$$

$$\boldsymbol{x_{ij}} \in \left\{0,\, 1\right\}\,;\,\forall(\boldsymbol{i},\boldsymbol{j}) \in \boldsymbol{A} \tag{19}$$

3. Results & discussion

First, an optimization model of transport costs and CO_2 emissions is developed. Subsequently, the index modules, parameters, and limitations/constraints are set. The initial step of the optimization is to perform a route search by minimizing the transportation cost (Z_1). Subsequently, minimization of the CO_2 emissions (Z_2) is continued using the same method as that used for the Z_1 optimization. Based on the Z_1 and Z_2 optimization results, the relationship between the transportation cost and CO_2 emission is analyzed.

3.1. *Constant speed case*

3.1.1. *Transportation cost and CO_2 emission in Z_1 minimization scenario*

The distribution route in the Z_1 minimization scenario tends to maximize the utilization of a transit terminal (locations 3–6). MR ships 4–8 are dedicated to the transit terminals as departure and return points. The supplies from the Kasim refinery (location 2) are transferred directly to the distribution centers in northern and southern Papua. The distribution routes are listed in Table 4.

Based on the optimum routes mentioned above, the charter cost constitutes approximately 63% of the total transportation cost

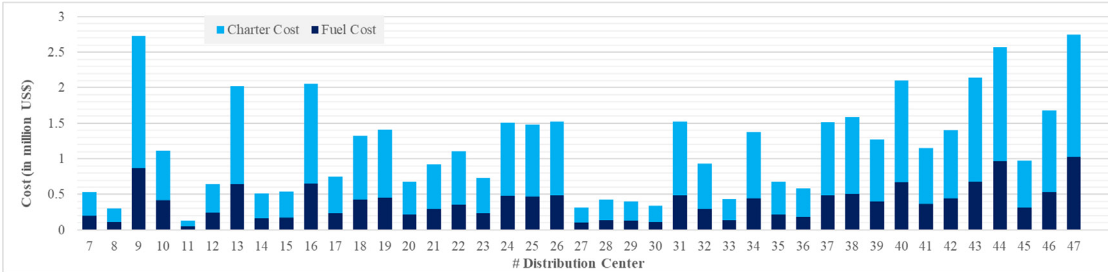

Fig. 4. Transportation Cost per Destination in Z_2 Minimization Scenario.

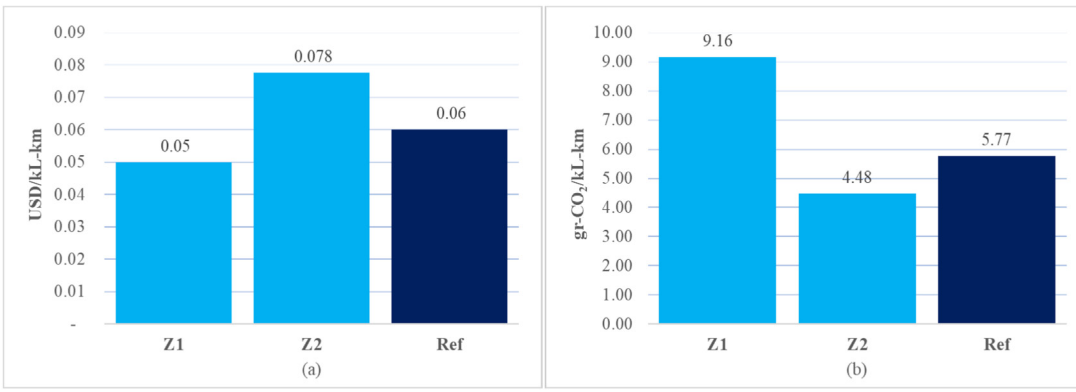

Fig. 5. Intensity of Cost per kL-km (a) and CO_2 per kL-km (b) in Z_2 Minimization Scenario.

(Fig. 2). The transportation costs to Sanana (location 31), Ternate (location 33), and Masohi (location 35) are the highest, owing to the long distances and relatively low demand volumes.

The Z_1 minimization scenario results in a total transportation cost of 26,909,780 USD or 0.05 USD/kL-km, which is lower than the transportation cost performance of Pertamina (0.06 USD/kL-km), as estimated using an escalation of 3% per year from (Ening, 2005). When Z_1 is minimized, the CO_2 emissions from the transportation infrastructure are 4,350,735 kg, which is equivalent to 9.16 gr-CO_2/kL-km. This is higher than the emissions from global ship transportation, which is 5.77 gr-CO_2/kL-km for average GP and MR vessels (Psaraftis & Kontovas, 2009). In summary, the Z1 minimization scenario results, as displayed in Fig. 3, show that the transportation cost can be minimized *via* distribution route optimization; however, it results in a high CO_2 intensity.

3.1.2. Transportation cost and CO_2 emissions in Z_2 minimization scenario

The distribution routes in the Z_2 minimization scenario are listed in Table 5. In this scenario, the tankers prefer to deliver directly from the Balikpapan refinery (location 1) to the distribution centers. The transit terminal locations (locations 3–6) are only utilized as sources of supply to meet the small portion of demand from the distribution centers. Hence, only MR ships 5–8 are dedicated to the transit terminals as the departure and return points. Concurrently, the supply route from the Kasim refinery (location 2) is the same as that for the Z_1 minimization scenario.

Based on the distribution routes in Table 5, the transportation cost for each destination is higher than the corresponding cost in the Z_1 minimization scenario; the charter cost accounts for 67% of the total cost of transportation, as shown in Fig. 4.

The Z_2 minimization scenario results in total CO_2 emissions of 3,725,230 kg or 4.48 g-CO_2/kL-km, with a total transportation cost of 62,732,168 USD or 0.078 USD/kL-km. The CO_2 emissions are lower than the global ship transport reference, which is 5.77 g-CO_2/kL-km for average GP and MR vessels (Psaraftis & Kontovas, 2009). However, the cost is higher because of the higher route mileage, thus increasing the cost of chartering ships, which is a function of time. In summary, the Z_2 minimization results, as presented in Fig. 5, show that although the CO_2 emissions can be minimized through distribution route optimization, there is an increase in the transportation cost.

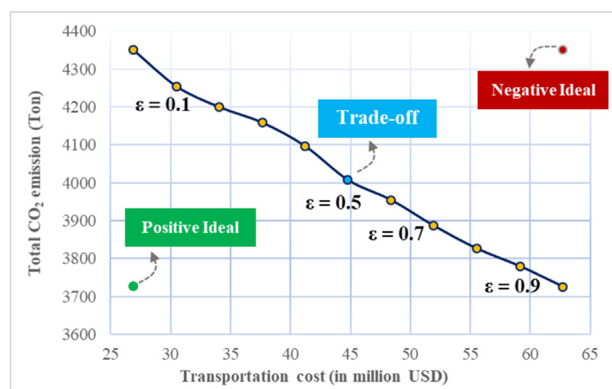

Fig. 6. Pareto Optimal Front Curve.

3.1.3. MOO scenario

Based on the results of the single-objective optimization, it can be concluded that the two objective functions are conflicting. The study shows that the total cost is optimal by maximizing the utilization of transit terminal while the emission is minimized when the shipping is direct. Thus, MOO is conducted to obtain the best possible solution that are compromised with each objective *i.e.* the trade off point. Several solution values are obtained, as shown in Fig. 6. The ideal positive point on the Pareto curve is (26.91; 3725), and the ideal negative point is (62.7; 4350). The trade-off value is obtained at ε = 0.5 based on the largest closeness coefficient (C_i) obtained using the TOPSIS method. The C_i value indicates that the

Table 5
Distribution Routes in Z_2 Minimization Scenario.

Ship	Route	Ship	Route
MR 1	1 → 12 → 26 → 28 → 35 → 42 → 41 → 1	MR 5	6 → 34 → 44 → 16 → 37 → 6
MR 2	1 → 11 → 21 → 4 → 1	MR 6	5 → 18 → 29 → 27 → 46 → 9 → 5
MR 2	1 → 47 → 15 → 14 → 5 → 20 → 1	MR 7	3 → 8 → 32 → 30 → 33 → 4 → 3
MR 3	1 → 7 → 38 → 13 → 22 → 6 → 1	MR 8	4 → 22 → 23 → 24 → 25 → 4
MR 3	1 → 31 → 17 → 38 → 1	GP 1	2 → 40 → 39 → 41 → 36 → 2
MR 4	1 → 10 → 19 → 3 → 1	GP 2	2 → 43 → 45 → 46 → 47 → 2

Table 6
Result of Proximity Coefficient Pareto Front Solution.

ε	Cost ($\times 10^6$ USD)	CO_2 emissions ($\times 10^6$ kg)	S_+	S-	C
1	62.73	3.73	35.82	62.55	0.50
0.9	59.15	3.78	32.69	57.28	0.51
0.8	55.57	3.83	30.37	53.00	0.52
0.7	51.99	3.89	29.77	47.74	0.51
0.6	48.40	3.95	31.41	42.15	0.51
0.5	44.82	4.01	33.37	38.78	0.54
0.4	41.24	4.10	39.79	33.30	0.51
0.3	37.66	4.16	44.66	31.58	0.52
0.2	34.07	4.20	48.00	32.39	0.52
0.1	30.49	4.25	53.08	33.64	0.52
0	26.91	4.35	62.55	35.82	0.50

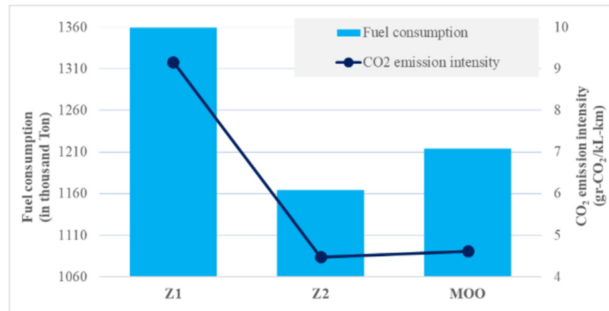

Fig. 8. Relationship Between Ship Fuel Consumption and CO_2 Emissions.

trade-off point has the smallest Euclidean distance to the ideal positive point (S_{i+}) and the farthest distance to the negative-ideal point (S_{i-}), as can be inferred from Table 6 (Rangaiah et al., 2020).

The logistics distribution routes based on the trade-off point in the MOO scenario are listed in Table 7, which shows that several distribution routes involve direct delivery from the Balikpapan refinery (Location 1) to the distribution centers in north Maluku and northern Papua to optimize the ship capacity utilization. Most other routes tend to be the same as those in the Z_1 minimization scenario, which optimizes the routes with supply sources from the transit terminals (locations 3–6) to fulfill most of the demand. Hence, MR ships 4–8 ships are dedicated to the transit terminals as the departure and return points. The supply route from the Kasim refinery (location 2) is the same as that in the Z_1 minimization scenario, which transfers products directly to the distribution centers in northern and southern Papua.

Deliveries to the Donggala depot (13) and Parigi (24) result in higher transportation costs than deliveries to other locations, as shown in Fig. 7. This is because of the considerably higher mileage and relatively lower demand volume for the former destinations. Based on the distribution pattern of each scenario, the fuel consumption of a ship in the MOO scenario is intermediate between those in the Z_1 and Z_2 minimization scenarios, as seen in Fig. 8. Based on the figure, the MOO scenario also minimizes the fuel costs and the CO_2 emissions of the ships simultaneously.

The MOO scenario results in a total cost of transportation of 44,820,974 USD or 0.053 USD/kL-km and total CO_2 emissions of 4,006,779 tons or 4.77 g-CO_2/kL-km; these results are intermediate between those obtained in the Z_1 and Z_2 minimization scenarios and are lower than the reference values. The results are summarized in Fig. 9.

The MOO scenario results in optimum logistics distribution routes, with the transportation cost and the CO_2 emissions being 11% and 17% lower than the reference values, respectively. Hence,

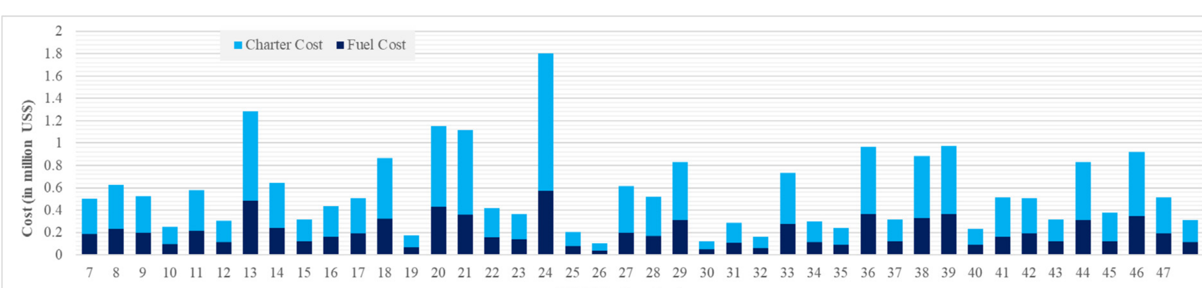

Fig. 7. Transportation Cost per Destination in MOO Scenario.

Table 7
Distribution Routes in MOO Scenario.

Ship	Routes	Ship	Routes
MR 1	1 → 12 → 20 → 21 → 13 → 1	MR 5	5 → 16 → 17 → 31 → 32 → 44 → 5
MR 2	1 → 7 → 1	MR 6	6 → 32 → 33 → 34 → 29 → 6
MR 2	1 → 5 → 27 → 28 → 11 → 1	MR 7	3 → 8 → 9 → 10 → 3
MR 3	1 → 14 → 15 → 47 → 45 → 34 → 1	MR 8	4 → 22 → 23 → 24→ 25 → 26 → 4
MR 3	1 → 5 →18 → 19 → 6 → 1	GP 1	2 → 43 → 46 → 36 → 2
MR 4	6 → 30 → 35 → 40 → 41 → 6	GP 2	2 → 39 → 38 → 42 → 37 → 2

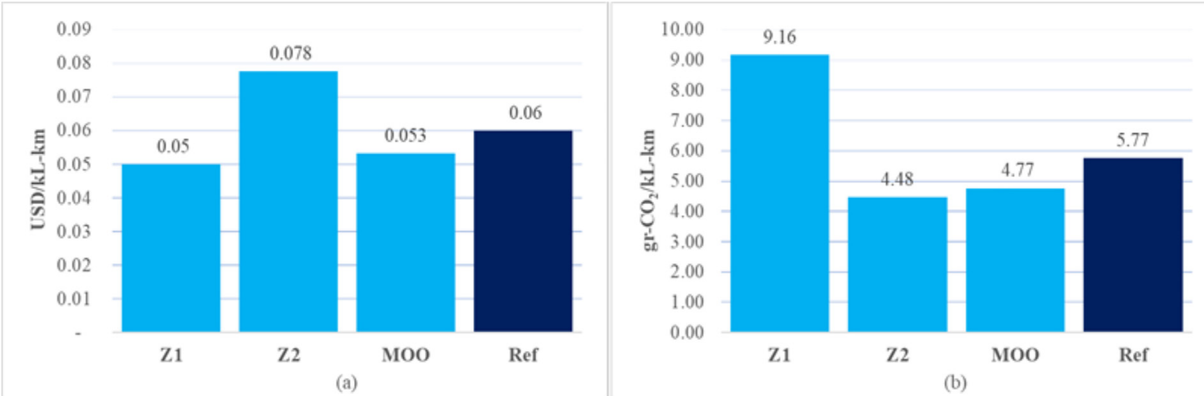

Fig. 9. Comparison of Intensity of Cost per kL-km (a) and CO_2 per kL-km (b) in All Scenarios with Current Condition.

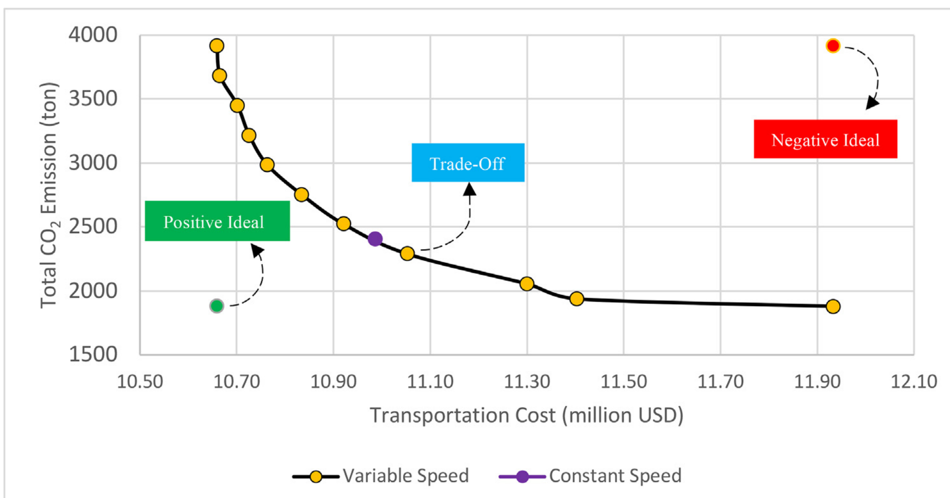

Fig. 10. Pareto Optimal Front Curve for Variable Speed Case.

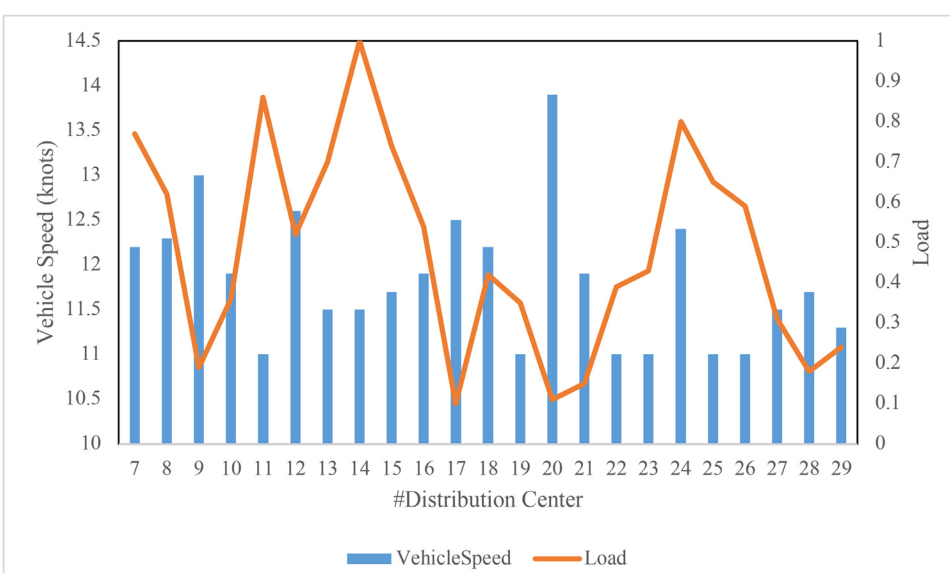

Fig. 11. Speed and Load of the Ships at Each Distribution Center.

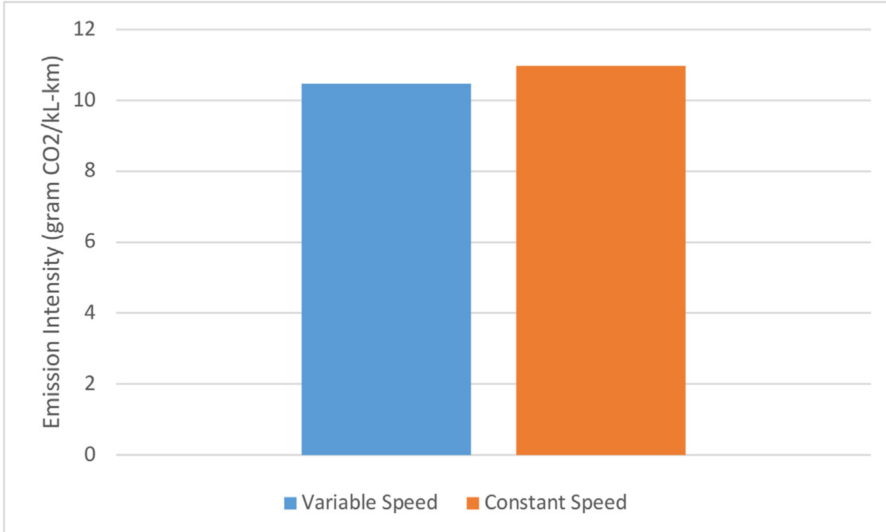

Fig. 12. Comparison of Emission Intensity in Constant and Variable Speed Case.

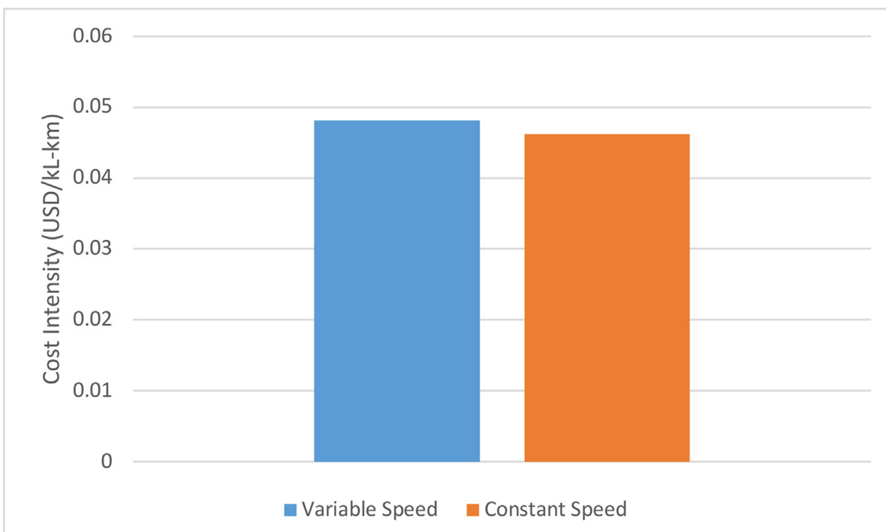

Fig. 13. Comparison of Cost Intensity in Constant and Variable Speed Case.

the MOO approach can be adopted by Indonesian institutions to implement green logistics, which can have a significant positive impact on the environment and the economy, considering that maritime logistics contributes the most to pollution worldwide (IMO, 2014).

3.2. *Variable speed case*

In the variable speed case, vehicle speed from point *i* to *j* acts as another decision variable. This case demonstrates the effect of using variable speed instead of constant speed on the cost and emissions. To perform this case, the system shown in Fig. 1 is simplified to only Kalimantan and Sulawesi (point 1,3,4,5,7–29). The decision to choose the Kalimantan and Sulawesi only due to the demand in those locations can only be supplied by 1 refinery thus it eliminates the variance of routes; hence the effect of variable speed can be examined without other factors interfering. Based on the fuel consumption equation retrieved from (Bialystocki & Konovessis, 2016), the vehicle speed ranges from 11 to 20 knots, and for the constant speed case vehicle speed of 12 knots is used.

The Pareto optimal front curve generated in this case can be seen in Fig. 10. The trade-off point is selected for the variable speed case, compared to the constant speed, variable speed emits less emission with slightly higher cost. The total cost of the variable speed option only costs 0.6% more than constant speed but emits 4.8% fewer emissions. In variable speed case, speed is inversely proportional to load (depicted in Fig. 11) meaning when the load of the ship is still high the speed is kept low to minimize the fuel consumption which leads to minimizing both objectives, and when the load of the ship is low, the speed can be maximized to minimize the cost, or the speed can be kept low to minimize emission. Higher vehicle speed, of course, contributing significantly to fuel cost, but higher speed makes charter cost decreases since the cruising time is shortened. Most of the cost is contributed by charter cost (Fig. 2, Fig. 4, and Fig. 7) consequently the strategy to use high speed in low loads is preferred to minimize the cost. However low speed is preferred to minimize CO_2 emissions since lower speed results in lower fuel consumption. Therefore, the strategy to variate the speed between one point to the point depending on the load can balance cost and CO_2. The strategy cannot be implemented in constant speed hence variable speed cases are preferred in the Pareto curve. Comparison of emission intensity and cost intensity of variable and constant speed is given in Fig. 12 and Fig. 13. Variable speed results in fewer emissions intensity and slightly higher cost intensity than the constant speed, this is in agreement with the Pareto curve depicted in Fig. 10.

4. Conclusion

In this study, the green logistics concept was analyzed by performing MOO of petroleum product logistics in a multi-depot system with a heterogeneous fleet. A trade-off between two conflicting objectives—transportation cost and CO_2 emissions—was studied. In addition, a comparison of cost and emissions between the variable and constant speed of ships is investigated. The optimization yielded optimum logistics distribution routes and the amount of products delivered.

For the constant speed case, the distribution routes obtained show that the minimizing cost scenario tends to maximize the utilization of transit terminals while the minimizing emissions scenario tends to deliver directly to the distribution centers, so the route decision in the MOO scenario is the combination of the two. In the minimizing cost scenario, the transportation cost intensity managed to be lower than the current transportation cost *i.e.* 0.05 USD/kL-km compared to 0.06 USD/kL-km and in the minimizing emissions scenario gives 4.48 g CO_2/kL-km, it is lower than the current value *i.e.* 5.77 g CO_2/kL-km. Whereas the MOO gives a compromises solution of cost and emissions with cost and emission intensity of 0.0573 USD/kL-km and 4.77 g CO_2/kL-km corresponding to 11% and 17% cost and emission reduction compared to the current value.

The comparison between constant and variable speed reveals that the variable speed is preferred to constant speed as it gives lower emissions with slight changes in cost.

Declaration of interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgments

The authors are grateful to DRPM UI for supporting work financially under the “Hibah Publikasi Terindeks Internasional (PUTI) Q2 Universitas Indonesia” year 2020, contract number NKB-1747/UN2.RST/HKP.05.00/2020.

Appendix A. List Locations and Coordinates

No.	Location	ID	Latitude (y)	Longitude (x)
1	Balikpapan refinery	BPP	−1.260872	116.812780
2	Kasim refinery	KSM	−1.307923	131.025588
3	Kotabaru (FSO)	FKB	−3.259063	116.423646
4	Terminal Bitung	BIT	1.439565	125.185196
5	Terminal Makassar	MKS	−5.112090	119.412116
6	Terminal Wayame	TTW	−3.664341	128.174614
7	Banjarmasin	BJM	−3.296325	114.567893
8	Sampit	SMP	−2.509876	112.978022
9	Pulang Pisau	PPS	−2.723898	114.262771
10	Kotawaringin, Pgk. Bun	PKB	−2.755131	111.719134
11	Samarinda	SAM	−0.502390	117.125471
12	Tarakan	TAR	3.283616	117.590959
13	Donggala	DON	−0.788886	119.802049
14	Pare - Pare	PAR	−4.001286	119.627343
15	Bau-Bau	BAU	−5.514754	122.555425
16	Palopo	PAL	−3.119019	120.261887
17	Kolaka	KOL	−4.04182	121.561894
18	Raha	RAH	−4.626766	122.715403
19	Kendari	KND	−3.969287	122.609873
20	Tolitoli	TOL	1.112435	120.779075
21	Tahuna	TAH	3.601882	125.49837
22	Gorontalo	GOR	0.510194	123.060638
23	Moutong	MOU	0.474581	121.244298
24	Parigi	PRG	−0.839153	120.190441
25	Poso	POS	−1.394616	120.717172
26	Ampana	AMP	−0.855236	121.598342
27	Luwuk	LUW	−0.940784	122.816056
28	Banggai	BAN	−1.586974	123.497737
29	Kolonedale	KDL	−1.979353	121.342547
30	Namlea	NAM	−3.272584	127.090604
31	Sanana	SAN	−1.987469	125.952925
32	Labuha	LAB	−0.628617	127.606892
33	Ternate	TER	0.756072	127.314432
34	Tobelo	TOB	1.622583	127.992704
35	Masohi	MAS	−3.295462	128.953107
36	Bula	BUL	−3.100226	130.504529
37	Saumlaki	SAU	−7.996069	131.285705
38	Dobo	DOB	−5.813979	134.252496
39	Kaimana	KAI	−3.657987	133.756393
40	Tual	TUL	−5.629387	132.742343
41	Fak-Fak	FAK	−2.924058	132.235441
42	Merauke	MKE	−8.473992	140.394421
43	Manokwari	MNK	−0.871503	134.058365
44	Biak	BIA	−1.184512	136.070678
45	Serui	SER	−1.883648	136.224861
46	Nabire	NAB	−3.349703	135.504715
47	Jayapura	JYP	−2.526692	140.726908

References

Bektaş, T., & Laporte, G. (2011). The pollution-routing problem. *Transportation Research Part B: Methodological*, *45*(8), 1232–1250.
Bialystocki, N., & Konovessis, D. (2016). On the estimation of ship's fuel consumption and speed curve: A statistical approach. *Journal of Ocean Engineering and Science*, *1*(2), 157–166. https://doi.org/10.1016/j.joes.2016.02.001
Bisschop, J. (2006). *AIMMS optimization modeling*. Lulu. com.
Demir, E., Bektaş, T., & Laporte, G. (2012). An adaptive large neighborhood search heuristic for the pollution-routing problem. *European Journal of Operational Research*, *223*(2), 346–359.
DRAOG. (2019). *Distribution pattern – Premium, kerosene and solar*. Downstream Regulatory Agency for Oil and Gas.
Ening. (2005). *Optimization of Petroleum Fuel Distribution Cost: Case Study of West Sumatera Province (in Bahasa)*. Universitas Indonesia. http://lib.ui.ac.id/detail?id=104864&lokasi=lokal
Eshtehadi, R., Fathian, M., & Demir, E. (2017). Robust solutions to the pollution-routing problem with demand and travel time uncertainty. *Transportation Research Part D: Transport and Environment*, *51*, 351–363. https://doi.org/10.1016/j.trd.2017.01.003
Hellenic Shipping. (2019). *Weekly tanker time charter estimates*.
Hickman, J., Hassel, D., Joumard, R., Samaras, Z., & Sorenson, S. (1999). *Methodology for calculating transport emissions (Issue SE/491/98)*.
IMO. (2014). *Third IMO greenhouse gas study 2014*.
IMO. (2019). *Greenhouse gas emissions*. Marine Environment.
Jabali, Ola, Van Woensel, Tom, & de Kok, A. G. (Ton). (2012). Analysis of Travel Times and CO_2 Emissions in Time-Dependent Vehicle Routing. *Production and Operation Management*, *21*(6) https://doi.org/10.1111/j.1937-5956.2012.01338.x
Kramer, R., Subramanian, A., Vidal, T., & Cabral, L. D. A. F. (2015). A matheuristic approach for the Pollution-Routing Problem. *European Journal of Operational Research*, *243*(2), 523–539. https://doi.org/10.1016/j.ejor.2014.12.009
Kuo, Y., & Wang, C. C. (2011). Optimizing the VRP by minimizing fuel consumption. *Management of Environmental Quality: An International Journal*, *22*(4), 440–450. https://doi.org/10.1108/14777831111136054
Lotov, A. V., & Miettinen, K. (2008). *Visualizing the Pareto Frontier*. pp. 213–243. https://doi.org/10.1007/978-3-540-88908-3_9
Mavrotas, G. (2009). Effective implementation of the ε-constraint method in Multi-Objective Mathematical Programming problems. *Applied Mathematics and Computation*, *213*(2), 455–465. https://doi.org/10.1016/j.amc.2009.03.037
Network for Transport Measures. https://www.transportmeasures.org/en/wiki/manuals/sea/fuel-consumption-as-a-function-of-load/, 2021
Pertamina. (2018). *Laporan Tahunan 2018*.
Psaraftis, H. N. (2016). Green maritime logistics: The quest for win-win solutions. *Transportation Research Procedia*, *14*, 133–142. https://doi.org/10.1016/j.trpro.2016.05.049
Psaraftis, H. N., & Kontovas, C. A. (2009). CO2 emission statistics for the world commercial fleet. *WMU Journal of Maritime Affairs*, *8*(1), 1–19. https://doi.org/10.1007/BF03195150

Psaraftis, H. N., & Kontovas, C. A. (2013). Speed models for energy-efficient maritime transportation: A taxonomy and survey. *Transportation Research Part C: Emerging Technologies*, *26*, 331–351. https://doi.org/10.1016/j.trc.2012.09.012

Rabbani, M., Tahaei, Z., Farrokhi-Asl, H., & Saravi, N. A. (2018). Using meta-heuristic algorithms and hybrid of them to solve multi compartment vehicle routing problem. In *IEEE International Conference on Industrial Engineering and Engineering Management, 2017-Decem* (pp. 1022–1026). https://doi.org/10.1109/IEEM.2017.8290047

Rai, G. (2013). *Behavioural chartering strategies*. Erasmus University Rotterdam.

Rangaiah, G. P., Feng, Z., & Hoadley, A. F. (2020). Multi-objective optimization applications in chemical process engineering: Tutorial and review. *Processes*, *8*(5) https://doi.org/10.3390/PR8050508

Sbihi, A., & Eglese, R. W. (2007). Combinatorial optimization and green logistics. *A Quarterly Journal of Operations Research*, *5*, 99–116.

Ship & Bunker. (2020). *World bunker prices*.

Shiptraffic.net. (2020). *Distance calculator*.

Wang, Z., & Rangaiah, G. P. (2017). Application and Analysis of Methods for Selecting an Optimal Solution from the Pareto-Optimal Front obtained by Multiobjective Optimization. *Industrial & Engineering Chemistry Research*, *56*(2), 560–574. https://doi.org/10.1021/acs.iecr.6b03453

Wang, S., Tao, F., & Shi, Y. (2018). Optimization of inventory routing problem in refined oil logistics with the perspective of carbon tax. *Energies*, *11*(6) https://doi.org/10.3390/en11061437