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A Novel Hybrid Spotted Hyena Optimizer: An Algorithm for Fuel Consumption Capacitated Vehicle Routing Problem

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Abstract. Distribution activities are closely related to the objective function of minimizing fuel consumption, which is affected by distance and product load in transportation. This indicates the need for optimization to improve company performance. Therefore, this study aims to develop a new Hybrid Spotted Hyena Optimizer (HSHO) algorithm, to minimize the total transportation and fuel costs. This was provided by applying the Large Rank Value (LRV) procedure to convert hyena positions to travel sequences. This also proposed a Flip and Swap rule in each iteration to improve the algorithm's performance. Furthermore, a mathematical model was developed for the Fuel Consumption Capacitated Vehicle Routing Problem (FCCVRP) by considering the load and FC (fuel consumption) rates between the nodes. This indicated that several population variations, iterations, and several nodes were used to investigate the effectiveness of the HSHO algorithm. The results showed increased population parameters, and HSHO iterations reduced the FCCVRP total transportation costs. Furthermore, decreasing the fuel consumption rate between nodes affected reduced fuel consumption. In addition, the proposed HSHO produced a more optimal total transportation cost than the state-of-the-art algorithm.

Keywords: Capacitated vehicle routing problem; Distribution; Fuel consumption; Spotted hyena optimizer

1. Introduction

The supply chain reportedly plays a vital role in organizational performance (Abdulameer, Yaacob, and Ibrahim, 2020; Ibrahim *et al.* 2020), through some activities such as procurement (Deepradit *et al.,* 2020), production scheduling (Utama *et al.,* 2019), and transportation (Sitompul and Horas, 2021; Benyamin, Farhad, and Saeid, 2021), where fuel consumption is found to be a crucial factor (Özener and Özkan, 2020; Norouzi, Sadegh-Amalnick, and Tavakkoli-Moghaddam, 2017). According to Sahin *et al.* (2009), a road transportation company in Shanghai, China, was responsible for 67.41% of fuel consumption within the total cost. This indicated that distribution route planning was a crucial factor to be considered in transportation activities (Utama *et al.,* 2020a), due to significantly affecting efficiency (Utama *et al.,* 2020c) and environmental protection (Dewi and Utama, 2021). Subsequently, most theories state that environmental problems are influenced by fuel consumption (Utama *et al.,* 2021b), indicating that the transportation sector should contribute to the reduction of energy utilization. In popular routing activities, the issue of

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reducing fuel consumption is known as the FCCVRP (Fuel Consumption Capacitated Vehicle Routing Problem) (Utama *et al.*, 2021a).

This was initially introduced by Kuo (2010), which proposed the Simulated Annealing (SA) procedure until several studies began to provide metaheuristic and heuristic algorithms as solution sources. The techniques utilized in these studies included Particle Swarm (PSO) (Poonthalir and Nadarajan, 2018) and Ant Colony Optimizations (ACO) (Yao *et al.*, 2015), Genetic Algorithm (GA) (Xiong, 2010), Simulated Annealing (SA) (Normasari *et al.*, 2019), Tabu Search (TS) (Suzuki, 2011), and the heuristic method Gaur, Mudgal, and Singh (2013). This indicated that the distance to estimate fuel consumption was generally considered, although it was still affected by the vehicle load between the nodes. In calculating fuel consumption, loads have recently been considered in several FCCVRP studies, indicating the development of metaheuristic algorithms such as SA (Xiao *et al.*, 2012), as well as Novel Hybrid TS (Niu *et al.*, 2018) and Hybrid PSO (Ali and Farida, 2021). These aligned with Zhang, Wei, and Lim (2015), where a local evolutionary search was provided for the problem. However, some previous FCCVRP studies assumed that the Fuel Consumption Rate (FCR) between nodes was similar, indicating that load and FCR subsequently affected FC (fuel consumption). This motivated several study experts to investigate the issues of the FCCVRP by developing a model emphasizing load-based inter-node FCR. These indicate that full load is considered by the FCR level between nodes during loading and no-load occurrences.

Therefore, this study aims to develop a Hybrid Spotted Hyena Optimizer (HSHO) to solve FCCVRP problems. This is because several studies did not use the algorithm to optimize Fuel Consumption Capacitated Vehicle Routing Problems. According to Dhiman and Kumar (2017), the inspiration obtained from the hunting behavior of hyenas led to the development of the SHO algorithm, which was applied in various fields (Ghafori and Gharehchopogh, 2021), such as allocation distribution (Naderipour *et al.*, 2021), scheduling (Şahman, 2021), and transportation salesperson problems (Nguyen *et al.*, 2020). This indicated that the algorithm was developed by integrating the neighborhood search procedure to solve FCCVRP. Therefore, the following contribution is observed (1) It proposes a new FCCVRP model balancing the payload and FCR between nodes, (2) It presents the influential analysis of the FCR on fuel consumption, and (3) It suggests a Novel HSHO developed from the integration of the SHO and neighborhood search procedures, respectively. The following sections are also observed, (a) Section 2 presents assumptions and problem definition, proposed algorithm, data collection, and experiment setup, (b) Section 3 explains the results and discussion, and (c) Section 4 shows the conclusions and recommendations for further studies.

2. Method

2.1. Assumptions and Problem Definition

Based on this study, several assumptions of FCCVRP were observed as follows: (1) The deterministic customer demand, (2) The FCR between nodes is affected by load weight, (3) Each customer is served once by one vehicle, (4) Each vehicle departs and returns to the depot, and (5) The vehicle type is homogeneous. Several notations were also used to define the FCCVRP, as shown below:

TC : Total Cost transportation (IDR)
V : Set of customers
Fx_k : Fixed cost for k-th route k (IDR)
$V0$: Set of customers and agents: $V0 = V \cup \{0\}$

K	: Set of route/vehicles
k	: Number of route/vehicles
n	: Number of customers: $n = \|V\|$
Di	: Demand customer i; $i = 1,2,3,\ldots,n$ (kilogram)
q_{ijk}	: The load carried from node i to j in route k (kilogram)
ρ_{ij}	: FCR from node i to j when the vehicle is unloaded (liter)
d_{ij}	: The distance from node i to j (kilometer)
p_{ij}^{*}	: FCR from node i to j when the vehicle is fully loaded (liter)
G_m	: Maximum vehicle load capacity (kilogram)
c_0	: Fuel cost per liter (IDR/L)
x_{ijk}	: binary variables (0.1) from node i to j, using vehicle k

The FCCVRP mathematical model was also developed from the method proposed by Xiao *et al.* (2012). It was developed by considering the node-dependent FCR. The objective function of the proposed model is formulated in Equation (1). Constraints of the proposed mathematical model are presented in Equations (2)-(7), with the model being developed as follows:

Objective function:

$$Min\, TC = \sum_{k=1}^{K}\sum_{i=0}^{n}\sum_{j=0}^{n}(Fx_k + (c_0.p_{ij} + \frac{p_{ij}^{*} - p_{ij}}{G_m}.q_{ijk}.d_{ij}.x_{ijk})) \tag{1}$$

Subject to:

$$\sum_{k\in K}\sum_{i\in V} x_{ijk} = 1, \forall j \in V \tag{2}$$

$$\sum_{i\in V} x_{ijk} - \sum_{i\in V} x_{jik} = 0, \forall j \in V, \forall k \in K \tag{3}$$

$$\sum_{i\in V} q_{ijk} = \sum_{i\in V}\sum_{j\in V} x_{ijk}\, D_i, \qquad \forall k \in K \tag{4}$$

$$\sum_{j=0, j\neq i, i\in V} q_{ijk} \leq G_m, \qquad \forall k \in \tag{5}$$

$$D_i \geq 0 \qquad i = 0,1,\ldots,n \tag{6}$$

$$x_{ijk} = \begin{cases} 1, & \text{visit node i to node j using vehicle k} \\ 0, & \text{otherwise} \end{cases} \tag{7}$$

Based on Equation (1), the reduction of the Total Cost (TC) was the objective function to be achieved in this study. This indicated that the fixed budgets (travel and fuel costs) were involved at the TC. Subsequently, the proposed fuel cost considered the nodal FCR, distance, price, and transported load quantity. The constraints of the FCCVRP mathematical model used were as follows: (i) *Constraint (2)* ensured that each customer was only visited by one vehicle, (ii) *Constraint (3)* indicated that vehicles should come and go from each customer, (iii) *Constraint (4)* showed that a load of all vehicles was equal to the demand from all customers, (iv) *Constraint (5)* stated that the loads did not exceed the maximum vehicle capacity, (v) *Constraint (6)* ensured that customer demand should not be negative, and (vi) *Constraint (7)* was the decision variable's binary number [0.1].

2.2. Hybrid Spotted Hyena Optimization (HSHO) Algorithm

This study proposed HSHO as a novel algorithm to solve the FCCVRP through the integration of the model and Neighborhood search implemented by Dhiman and Kumar (2017). This algorithm had five (5) main phases, namely (1) circling prey, (2) hunting, (3) attacking prey (exploitation), (4) searching for prey (exploration), and (5) neighborhood search. In the circling prey phase, the position of the spotted hyena was formulated in Equation (8), while a herd surrounding the prey was shown in Eqs. (9) and (10). This indicated that $\vec{P}$ and r = the position vector of the spotted hyena and a random number [0.1], X_{max} and X_{min} = the upper and lower bounds, $\vec{D}h$ = the distance between the prey and spotted hyena, x = the current iteration, $\vec{B}$ and $\vec{E}$ = the coefficient vectors, and $\overrightarrow{Pp^*}$ = the position vector of the prey. In addition, $\vec{B}$ and $\vec{E}$ were calculated based on Eqs. (11)-(13), where $\overrightarrow{rd1}$ and $\overrightarrow{rd2}$ were random numbers [0.1].

$$\vec{P} = X_{min} + r \times (X_{max} - X_{min}) \tag{8}$$

$$\vec{D}h = \left|\vec{B}.\overrightarrow{Pp^*}(x) - \vec{P}(x)\right| \tag{9}$$

$$\vec{P}(x+1) = \overrightarrow{Pp^*}(x) - \vec{E} \cdot \overrightarrow{Dh} \tag{10}$$

$$\vec{B} = 2 \cdot \overrightarrow{rd1} \tag{11}$$

$$\vec{E} = 2\vec{h} \cdot \overrightarrow{rd2} - \vec{h} \tag{12}$$

$$\vec{h} = 5 - (\text{Iteration} * (5/\text{maxiteration})) \tag{13}$$

According to the hunting phase, the best and optimal spotted hyenas had good knowledge (fitness) of prey locations. This showed that the herd created a cluster towards the best hyena, indicating the subsequent updates of their positions. These behaviors were modeled in Equations (14) to (16), where $\overrightarrow{Ph}$ = the position of the initial best hyena, $\overrightarrow{Pk}$ = the position of other hyenas, N = the number of spotted hyenas, calculated according to Equation (17), M = a random value (0, 5.1), nos = the number of solutions after the addition of M, and $\overrightarrow{Ch}$ = the group or cluster of N-solutions.

Based on a discrete problem classified as a hard non-polynomial issue, the decision variable of FCCVRP was observed as the sequence of trips. This indicated the development of the Large Rank Value (LRV), to convert the position of the spotted hyena vector to the travel order. It is also an easy method to convert continuous values to the combinatorial problem, i.e., sorting from the largest to the smallest (Utama and Widodo, 2021). The conversion of the spotted hyena position to the travel route is shown in Figure 1. In addition, the results of the trip sequence for each predator were used to calculate the total distribution cost in Equation (1).

$$\overrightarrow{Dh} = \left|\vec{B}.\overrightarrow{Ph} - \overrightarrow{Pk}\right| \tag{14}$$

$$\overrightarrow{Pk} = \overrightarrow{Ph} - \vec{E}.\overrightarrow{Dh} \tag{15}$$

$$\overrightarrow{Ch} = \overrightarrow{P_k} + P_{k+1} + \ldots\ldots + \overrightarrow{P_{k+N}} \tag{16}$$

$$N = count_{nos}(\overrightarrow{Ph}\ , \overrightarrow{P_{h+1}}, \overrightarrow{P_{h+2}} \ldots \overrightarrow{P_{h+m}}) \tag{17}$$

In the attacking prey (exploitation) phase, the observations were modeled in Equation (18), where $\vec{P}(x+1)$ was determined as the new position of the spotted hyena. This indicated a decrease in the value of $\vec{h}$, as $\vec{E}$ changed with each additional iteration. It also showed that the herd moved away and closer to locate and attack the prey. When the value of |E|<1, E was subsequently generated from a variational random number [-1, 1]. In the searching phase (exploration), the spotted hyenas predictably moved away from the prey when the value of |E|>1.

$$\vec{P}(x+1) = \frac{\vec{Dh}}{N} \tag{18}$$

According to the neighborhood search phase, an exchange was applied to improve the algorithm performance in each iteration (Utama *et al.,* 2020b). This indicated that two neighborhood exchange rules were proposed in this study, namely flip and swap, where a reversal was observed by transforming and exchanging two randomly selected position vectors of the spotted hyenas, as shown in Figures 2 and 3, respectively. The repetition of the neighborhood search was also suggested as 0.25 x the number of customers in each iteration. The LRV process was also applied as regards the conversion to a sequence of trips on each iteration. This was then compared with the previous processes to determine the best solution in the present iteration. In addition, algorithm 1 presented the complete Pseudo-code of the HHSO model, whose flow chart is shown in Figure 4.

Algorithm 1 Pseudo-code Hybrid Spotted Hyena Optimizer

```
Input: the spotted hyenas population P i ( i = 1 , 2 , . . . , n )
Output: the best search agent
procedure SHO
Initialize the parameters h, B, E, and N
Calculate the fitness of each search agent
Ph_best = the best search agent
Ch_best = the group or cluster of all far optimal solutions
    while ( x < Max number of iterations ) do
      Attacking prey (exploitation) includes the hunting phase
        for each search agent, do
          Update the position of the current agent by Equation (18)
        end for
      Search for prey(exploration) include Encircling prey
      Update h, B, E, and N
      Check if any search agent goes beyond the given search space and then adjust it
      Calculate the fitness of each search agent
      Update P h if there is a better solution than the previous optimal solution
      Update Ph_best and Ch_best
                for i = 0: 0.25 × customer number
                    Perform flip on Ph_i,best position
                    if (evaluate ( Ph_i,best) < evaluate ( Ph_best))
                          Ph_best = Ph_i,best
                  end if
                end for
                for i = 0: 0.25 × customer number
                    Perform swap on Ph_i,best position
                    if (evaluate ( Ph_i,best) < evaluate ( Ph_best))
                          Ph_best = Ph_i,best
                    end if
                end for
      x = x + 1
      end while
 return Ph_best
end procedure
```

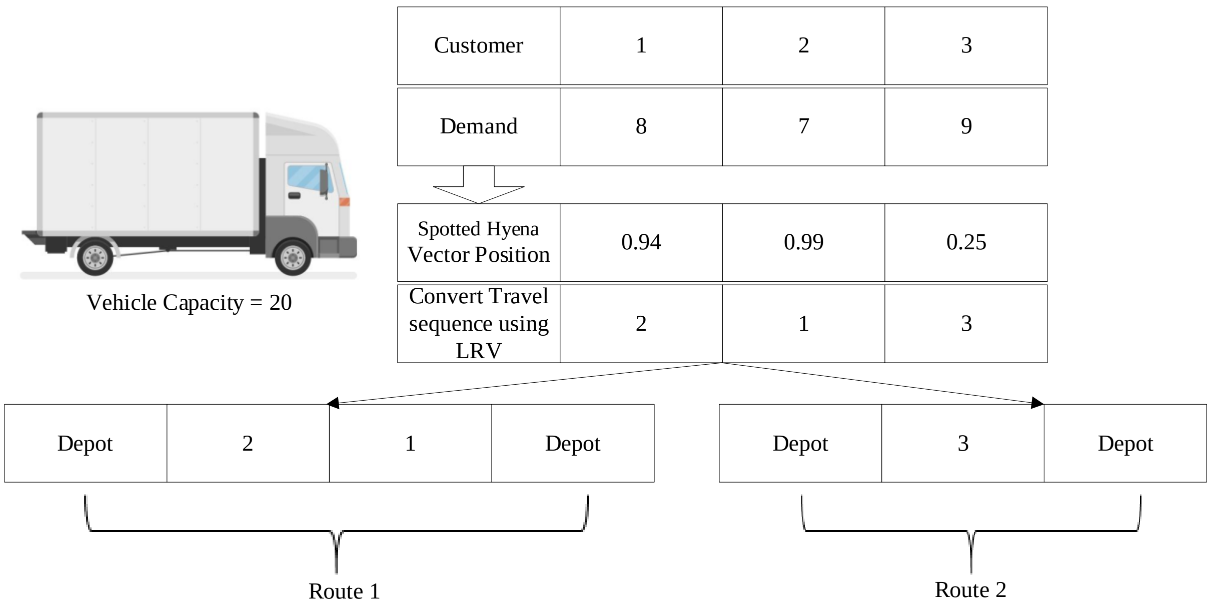

Figure 1 The conversion of the spotted hyena's position to the travel route

2.3. *Data Collection and Experiment Setup*

The data were obtained from the case study of a mineral water distribution company in Mojokerto, Indonesia, where the needs of 25 customers were to be met. The demand for each customer (Di) was between 379 and 905 kg, with the vehicle capacity (Gm) estimated to carry 2500 kg for one transport. The price of fuel per liter (c_0) was also IDR 9,400, with the fixed cost for delivery (Fx_k) being IDR 300,000. Furthermore, the company had 1 Distribution Centre (DC) for customer needs, as the distance observed between 1 DC and 25 consumers (d_{ij}) was within 0.5-52 km. The FCRs from node i to j were also observed between 0.313-0.714 L/km and 0.625-1.429 L/km when the vehicle was unloaded (p_{ij}) and fully loaded (p^*_{ij}), respectively. Based on the analysis, the iteration and population of HSHO were utilized with five variations each to test the parameters of this algorithm on the total cost of transportation. These five spotted hyena population parameters and HSHO iteration were applied between 50-500 and 10-200, respectively. In this test, approximately 25 trials were successfully conducted, with the best solution being stored for use in the sensitivity analyses. This test was subsequently used to examine the effect of the FCCVRP changes on the total, fixed, and fuel costs, respectively.

According to the sensitivity test, the transformed variables were p_{ij}, p^*_{ij} , c_0, and Fx_k. This indicated that the five variations of ρ_{0ij} and p^*_{ij} were shifted from the initial values at each node. In cases 1/2 and 4/5, the initial ρ_{ij} value was decreased and increased by 0.1/0.05 and 1/1.5, respectively, with condition 3 completely utilizing this value. The initial p^*_{ij} values were also decreased and increased by 0.1/0.05 and 1/1.5 in cases 6/7 and 9/10, respectively, with condition 8 fully using this value. In c_0, five data variations were applied with a value range of 8500 to 10500. Furthermore, five data variations were used for Fx_k between 150000-400000, as comparisons with the state-of-the-art algorithms were applied to test the performance of HSHO. Based on the case study data, random parameters were generated for d_{ij} , p_{ij} , *and* p^*_{ij} . This indicated the utilization of three variations, namely small (15 and 25 customers), medium (50 and 60 customers), and large (90 and 100 customers) cases, respectively. The utilized comparison algorithm was also SA (Kuo 2010), ACO (Yao *et al.,* 2015), GA (Xiong, 2010), HPSO (Ali and Farida, 2021), Teaching–Learning-Based Optimization (TLBO) (Trachanatzi *et al.,* 2021). These algorithms were then operated with 200 iterations and 500 population through the Matlab 2014a software on Windows 10 AMD A12 x64-64 8GB RAM processor.

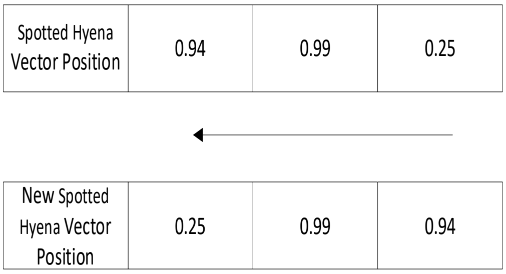

Figure 2 The illustration of the Flip rule

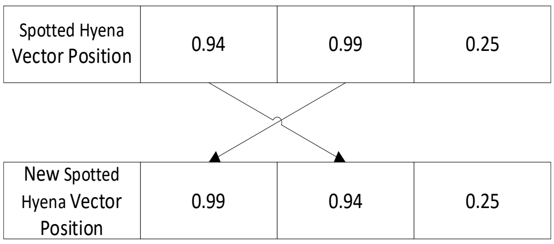

Figure 3 The illustration of the Swap rule

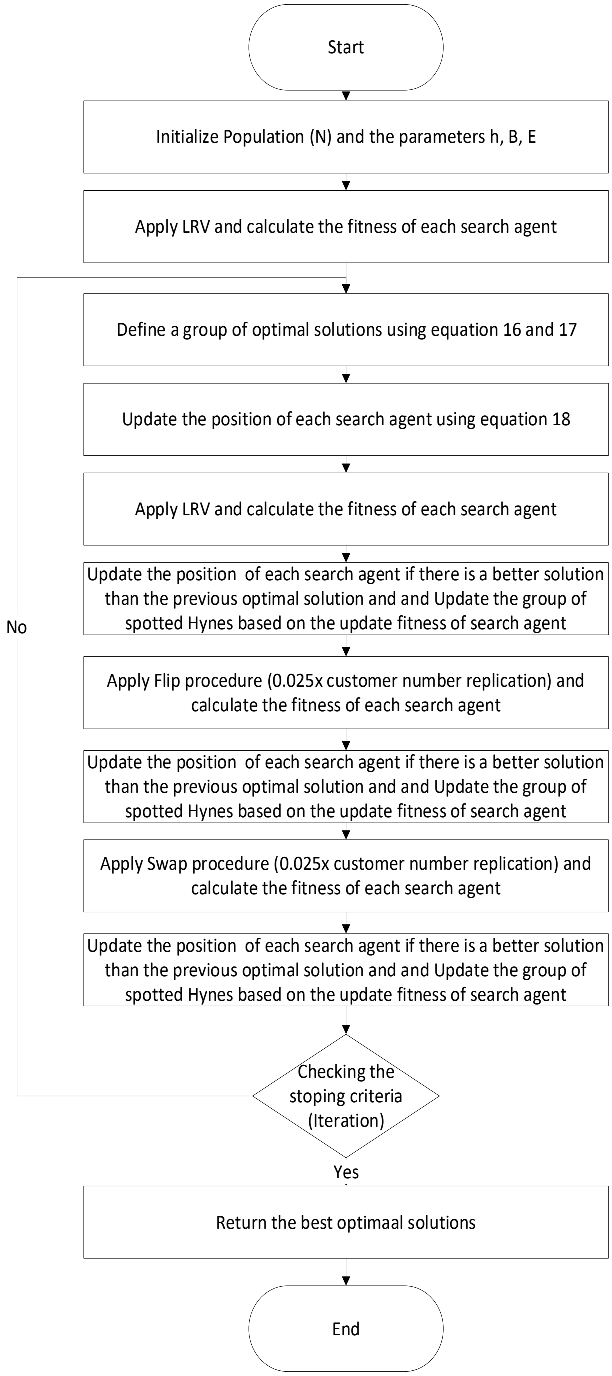

Figure 4 The proposed HHSO flow chart

3. Results and Discussion

3.1. Effect of HSHO Parameters on Total Transportation Cost

The results of the HSHO effects on the total cost of transportation are presented in Table 1, where increasing iterations and population of the algorithm reduced the TC. However, decreased iterations and populations led to high total transportation costs. This indicated that large population parameters and HSHO interactions were needed to solve the FCCVRP. For a population of 500 and 200 iterations, the optimal result of TC was generated, as six routes were produced with a total transportation cost of 3,128,100 IDR.

Table 1 The effects of HSHO on total transportation cost (IDR)

Population	Iteration				
	10	30	50	100	200
50	3,405,100	3,388,800	3,375,900	3,286,200	3,273,300
200	3,297,700	3,293,800	3,257,800	3,222,700	3,218,800
300	3,284,600	3,284,000	3,269,700	3,235,500	3,179,700
400	3,305,900	3,295,700	3,264,700	3,218,200	3,194,700
500	3,266,800	3,247,900	3,217,500	3,176,500	3,128,100

3.2. Sensitivity Analysis

The effects of the ρ_{ij} and p_{ij}^* value changes towards the cost are shown in Tables 2 and 3, respectively, where both parameters significantly affected the total transportation budget. When the values of ρ_{ij} and p_{ij}^* were increased and decreased, the total and fuel costs were also observed to be elevated and reduced, respectively. This indicated that the changes and the increase/decrease of both values significantly and insignificantly influenced the fuel and fixed costs, respectively. Therefore, the distribution company needs to minimize the ρ_{ij} and p_{ij}^* values, to optimize the total transportation cost.

Table 2 The effect of the ρ_ij value change towards the cost (IDR)

Case	Total Cost	Fixed Cost	Fuel Cost
Case 1 (-0.1)	2,954,500	1,800,000	1,154,500
Case 2 (-0.05)	3,041,300	1,800,000	1,241,300
Case 3 (initial case)	3,128,100	1,800,000	1,328,100
Case 4 (+1)	4,864,100	1,800,000	3,064,100
Case 5 (+1.5)	5,732,000	1,800,000	3,932,000

Table 3 The effect of the p_{ij}^* value change towards the cost (IDR)

Case	Total Cost	Fixed Cost	Fuel Cost
Case 6 (-0.1)	2,835,600	1,800,000	1,035,600
Case 7 (-0.05)	2,981,900	1,800,000	1,181,900
Case 8 (initial case)	3,128,100	1,800,000	1,328,100
Case 9 (+1)	4,590,500	1,800,000	2,790,500
Case 10 (+1.5)	5,321,700	1,800,000	3,521,700

The effect of the c_0 value change towards cost is presented in Table 4, where higher and lower c_0 led to more expensive and cheaper fuel and total transportation costs, respectively. This indicated that the c_0 value had no significant effect on the fixed cost.

Table 4 The effect of c_0 value change towards the cost (IDR)

c_0 (IDR/liter)	Total Cost	Fixed Cost	Fuel Cost
8,500	3,000,900	1,800,000	1,200,900
9,000	3,071,600	1,800,000	1,271,600
9,400	3,128,100	1,800,000	1,328,100
10,000	3,212,900	1,800,000	1,412,900
10,500	3,283,500	1,800,000	1,483,500

The results of the F_x value change towards the cost is shown in Table 5, where higher and lower F_x values led to more expensive and cheaper transportation and fixed costs, respectively. This indicated that fuel cost had no significant effect on F_x.

Table 5 The effect of F_x value change towards the cost (IDR)

Fx	Total Cost	Fixed Cost	Fuel Cost
150,000	2,228,100	900,000	1,328,100
200,000	2,528,100	1,200,000	1,328,100
300,000	3,128,100	1,800,000	1,328,100
350,000	3,428,100	2,100,000	1,328,100
400,000	3,728,100	2,400,000	1,328,100

3.3. Algorithm Comparison

Based on this study, a comparison of the HSHO algorithm was carried out against the SA, ACO, GA, HPSO, and TLBO algorithms. The comparative results towards the total transportation costs are shown in Table 6, where the proposed HSHO algorithm produced more optimal TC than the HPSO, TLBO GA, ACO, and SA algorithms. This was subsequently confirmed from the three variants of the trial case (small, medium, and large), which produced a better and optimal total transportation cost.

Table 6 Comparison of Algorithms to Total Transportation Costs (IDR)

Varian Case	Customer	Algorithm					
		SA	ACO	GA	HPSO	TLBO	HSHO
Small	15	**2,094,100**	**2,094,100**	**2,094,100**	**2,094,100**	**2,094,100**	**2,094,100**
	25	3,266,800	3,217,500	**3,128,100**	**3,128,100**	**3,128,100**	**3,128,100**
Medium	50	10,698,000	10,676,000	10,489,000	**9,749,700**	10,489,000	**9,749,700**
	60	13,404,000	13,113,000	12,895,000	12,553,000	12,553,000	**12,467,000**
Large	90	21,907,000	21,692,000	21,585,000	21,250,000	21,250,000	**21,218,000**
	100	25,042,000	24,698,000	24,137,000	23,589,000	24,137,000	**23,112,000**

4. Conclusions and Future Research

This study presented the FCCVRP that considered the load-based inter-node FCR. In this condition, a new mathematical model and algorithm (FCCVRP and HSHO) were proposed as solution sources. Moreover, the HSHO was a combination of the SHO algorithm with the neighborhood search procedure. Based on the numerical experiments in the model, the changes observed in ρ_{ij} and p_{ij}^* affected the total transportation costs. This indicated that the increase in population parameters and HSHO iterations optimized the total transportation costs in the FCCVRP. The comparative analysis of algorithms also showed that HSHO produced optimal solutions in small, medium, and large cases compared to other algorithms. However, the proposed algorithm had limitations in considering a single distribution center, commodity delivery, and a homogeneous vehicle. Effective computation time was also ignored in solving the FCCVRP, indicating that future studies should consider multi-distribution centers, multi-commodity products, and vehicle heterogeneity. In addition, computation time should be considered in problem-solving.

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