Completion of FCVRP using Hybrid Particle Swarm Optimization Algorithm

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ABSTRACT

The issue of green logistics has received full attention from the government and business people. It is closely related to the increase in Green House Gas (GHG) by transportation activities in the logistics sector. Controlling fuel consumption in transportation activities is fundamental in dealing with GHG. Therefore, the Fuel Consumption Vehicle Routing Problem (FCVRP) is proposed as a solution model in optimizing fuel consumption in the logistics sector. This study aims to develop a Hybrid Particle Swarm Optimization (HPSO) algorithm to solve the FCVRP problem. The proposed algorithm is the development of the PSO algorithm with local procedures search. Several experiments were carried out to determine the HPSO parameter's effect on minimizing fuel consumption in the FCVRP. The experiment results show that increasing the population and iteration parameters can produce minimum fuel consumption. Furthermore, the smaller the total fuel consumption produced when the kilometers per liter (KPL) high.

1. Introduction

Recently, the government and business players have increased their awareness of green logistics in the industrial sector [1]. The background of concern is based on the fact that logistics activities cause significant negative impacts on the environment [2]. Transportation is the most critical element in logistics and infrastructure fundamental to economic growth [3]. However, transportation also contributes to a large part of overall pollution [4]. In the last few decades, scientists have revealed that transportation activity causes an increase in Green House Gas (GHG) in the atmosphere [5]. Thus, the industrial sector's logistic policies need to consider environmental and ecological effects and focus on economic aspects.

According to Poonthalir and Nadarajan [6], fuel consumption in transportation activities is an essential parameter in controlling GHG. One of the main parameters affecting fuel consumption is the weight of load [7]. According to the US Department of Energy, Wang and Kuo [8] stated that fuel consumption increased by 2% for each additional 100-pound capacity. So that in this situation, logistics activities require a

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settlement model to minimize fuel consumption. One solution to this problem is to use the Green Vehicle Routing Problem (GVRP) [9]. GVRP can effectively increase fuel and pollutant efficiency by planning the proper routing of vehicles [10]. The GVRP variant demonstrating the importance of minimizing fuel consumption is called the Fuel Consumption Vehicle Routing Problem (FCVRP) [11].

Several studies have considered environmental aspects in most of the GVRP research. In this area, FCVRP is a new extension that reduces fuel consumption to reduce environmental impact. This study was first presented by Suzuki [12] by applying the Search Tabu (TS) to search for a solution. Xiao and Konak [13] completed the FCVRP model with the Simulated Annealing Algorithm. Several other solution approaches were used to solve the FCVRP problem, including intelligence heuristic partitioning by Gaur, et al. [7]. A gravitational search algorithm by MirHassani and Mohammadyari [14] to solve FCVRP. Several algorithms were proposed in other studies, such as the genetic algorithm proposed by Psychas, et al. [15], a firefly algorithm developed by Zhang, et al. [16]. In their study, Rao, et al. [17] used the Local Search hybrid to solve the FCVRP model. Meanwhile, Niu, et al. [18] utilized a novel hybrid Tabu Search algorithm.

Another study aimed to minimize the fuel consumption of a vehicle was presented by Kuo [19]. Kuo used the Simulated Annealing Algorithm to solve the time-dependent VRP. Xiao, et al. [20] also implemented a Simulated Annealing Algorithm. Other algorithms that have been used for this purpose were the genetic algorithm [21] and the ant colony algorithm [22]. Peng and Wang [23] also participated in the development of the FCVRP. Psychas, et al. [24] proposed a differential evolution algorithm, Eydi and Alavi [25] developed a mixed-integer linear programming model as a solution approach. The particle swarm optimization algorithm was used by Poonthalir and Nadarajan [6] to minimize the fuel consumption of the GVRP model. In the same model, Utama, et al. [3] utilized the hybrid butterfly optimization algorithm's development. Meanwhile, Dewi and Utama [10] proposed the development of a hybrid whale optimization algorithm. PSO was also used by Norouzi, et al. [26] to minimize fuel consumption with a time dependency. Research by Normasari, et al. [27] and Wang, et al. [28] used a Simulated Annealing Algorithm, slightly different from Andelmin and Bartolini [29], who chose to use the local search procedure. Macrina, et al. [30] proposed an extensive neighborhood hybrid as a way of finding solutions. In contrast, Wang and Lu [31] proposed a picking algorithm. Another study by Zhang, et al. [32] exercised the Tabu Search development.

Although research on GVRP continues to increase, studies related to FCVRP are still very limited. Research on this subject is mostly limited to the aspects of vehicle speed and travel distance. However, there is very little exploration of FCVRP research that focuses on the weight of the load. Looking at the gab, this study focuses on minimizing fuel consumption in the FCVRP study by considering the load aspect's weight. In addition, to our knowledge, there has been no previous research investigating studies related to FCVRP with the hybrid particle swarm optimization (HPSO) approach. Therefore, this research aims to minimize fuel consumption with HPSO as a solution approach. The contribution of this research is to propose a new hybrid particle swarm optimization procedure to solve the FCVRP problem. In addition, this study provides a careful investigation of the effect of kilometers per liter (KPL) on FCVRP.

This research's structure is presented as follows; Section (2) Method presents assumptions, notation and description of the problem, hybrid particle swarm optimization algorithm, and data and experiments. Section (3) Results and Discussion describes several topics such as hybrid particle swarm optimization solutions and changes in KPL on total fuel consumption. The last section is the conclusion of the entire research series and suggestions for further research.

2. Methods

2.1 Assumptions, Notations, and Problem Descriptions

The problem assumptions in the FCVRP problem are as follows; (1) Each customer is only served by one vehicle, (2) Each vehicle departs and returns to the depot (3) Fuel consumption is affected by the weight of the load, KPL, and distance (4) Vehicles for distribution activities are homogeneous (4) Demand for every customer is a regular.

To describe the FCVRP problem, this study uses the notations described as follows:

KPL : distance traveled per unit of fuel
p : fuel consumption increases with each additional load
k : increase in load capacity
L_{ij} : load
K : collection of vehicles at the depot, with $K = \{1,2, \dots, k$
R^k : set of routes traveled by the vehicle$k$, with $R = \{R^1, R^2, .., R^k\}$
V : set node
d_{ij} : distance from i to j nodes
r : route index
C_r^k : operational costs for vehicle k traveling the route r
A_{ri}^k : constant, value 1 if vehicle k with route r to customer i and value 0 for other conditions
T_k^r : time taken for the vehicle to travel the route r
T_{max} : maximum allowable travel time
FC : *Total Fuel Consumption*
R_r^s : sth node in rth route, for example $R_2^4 = 4$ can be interpreted as the 4th node on the 2nd route is 4 (0-5-2-3-4-0)

In this study, the problem description was described in a mathematical model. The objective function of this FCVRP problem was to minimize fuel consumption. The mathematical model that described the problem description is described as follows:

Objective function:

$$Minimize\ FC = \sum_{v \in V} \sum_{r \in R^v} \frac{d_{ij}}{KPL_{ij}} \left(1 + p\left(L_{ij}/k\right)\right)_r^k x_r^v \quad (1)$$

Constraint:

$$\sum_{k \in K} \sum_{r \in R^k} C_r^k x_r^k \geq 1 \qquad \forall\, i \in N \quad (2)$$

$$\sum_{k=1}^{K} y_{ik} = 1 \qquad \forall\, i \in V\,\{0\} \quad (3)$$

$$\sum_{k=1}^{K} y_{0k} = K \quad (4)$$

$$\sum_{i \in V} d_i y_{ik} \leq C_k \qquad \forall k = 1,2, \dots K \quad (5)$$

$$\sum x_r^k \geq 1 \qquad \forall\, k \in K \quad (6)$$

$$\sum_{r \in R^k} T_r^k X_r^k \leq T_{Max} \qquad \forall\ \mathrm{k} \in \mathrm{K} \quad (7)$$

$$x_r^k \in \{0,1\} \qquad \forall\, k \in K,\ \ \forall\, r \in R^k \quad (8)$$

With the decision variables:

$$x_r^k = \begin{cases} 1, & If\ \ vehicle\ k\ using\ r\ route \\ 0, & Other \end{cases}$$

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Equation (1) was the objective function to minimize fuel consumption. The constraint in Equation (2) was ensuring that all customers can be visited. Equation (3) guaranteed that each customer was served once by a vehicle. The limitation in equation (4) was to guarantee that K vehicles could carry out distribution activities. The constraint in equation (5) ensured that customer demand did not exceed the vehicle capacity on each route. Equation (6) was ensuring that every vehicle passed at least one lane/route. The constraint in equation (7) was to ensure that the vehicle travel time did not exceed the allowable travel time. Equation (8) was a constraint that guaranteed the decision variable x_r^k was a binary integer.

2.2 FCVRP Completion with Hybrid Particle Swarm Optimization (HPSO) Algorithm

This study suggested the use of the HPSO algorithm to minimize fuel consumption. The HPSO algorithm is a model development of the Particle Swarm Optimization (PSO) algorithm. The proposed algorithm combines PSO with a local search strategy. The PSO algorithm was initially proposed by Trelea [33] in 2003. Each particle has characteristics that distinguish PSO from other algorithms, namely position and velocity. NP-hard problems such as FCVRP require high computation time in line with the complexity of the study. The hybrid process in an algorithm can increase the effectiveness of finding a solution. Therefore, Hybrid PSO (HPSO) was proposed in this study to minimize fuel consumption in FCVRP problems.

HPSO has stages in its journey, such as (1) Converting particle positions into travel routes using the Short Rank Value (SRV) method (2) Updating inertia weight (3) Updating cognitive acceleration (4) Updating social acceleration (5) Updating velocity (6) Updating particle position (7) Conducting local search. The local search procedure used to develop the algorithm was the swap and flip procedure. The following is an explanation regarding the stages of HPSO in completing the FCVRP.

2.2.1 Convert particle position into travel route

The search for a solution began with initializing the position through a random number with an upper limit (ub) and a lower limit (lb). The upper limit (ub) and the lower limit (lb) were used to determine each particle's position. In this process, there should be no repetition of values in each position dimension. This illustration is presented in Fig. 1. The position value (continuous) was then converted into a trip sequence (discrete) using the SRV method. The way these method works was to sort the position values from the smallest to the largest value. Fig. 2 shows a representation of the SRV process.

$$P = \begin{Bmatrix} 0{,}56 & 0{,}91 & 0{,}85 \\ 0{,}77 & 0{,}39 & 0{,}75 \\ 0{,}42 & 0{,}12 & 0{,}55 \end{Bmatrix} \qquad P = \begin{Bmatrix} 0{,}56 & 0{,}91 & 0{,}85 \\ 0{,}77 & 0{,}91 & 0{,}75 \\ 0{,}42 & 0{,}12 & 0{,}55 \end{Bmatrix}$$

(a) (b)

Fig. 1. Initialization of the position value (a) accepted population (b) rejected population

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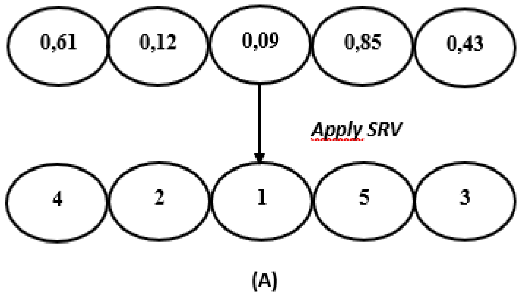

Fig. 2. SRV application (a) correct travel sequence (b) wrong travel sequence

The procedure for calculating fuel consumption can be seen in Fig. 3. The formula for calculating the fuel consumption was carried out by reversing the sequence of the sub-routes formed. Fig. 3 describes the sum of all customer requests distributed from the customer $R_n^{(e)}$ and followed by the next customer in reverse until customer $R_n^{(s)}$ and the last one visited was the distribution center.

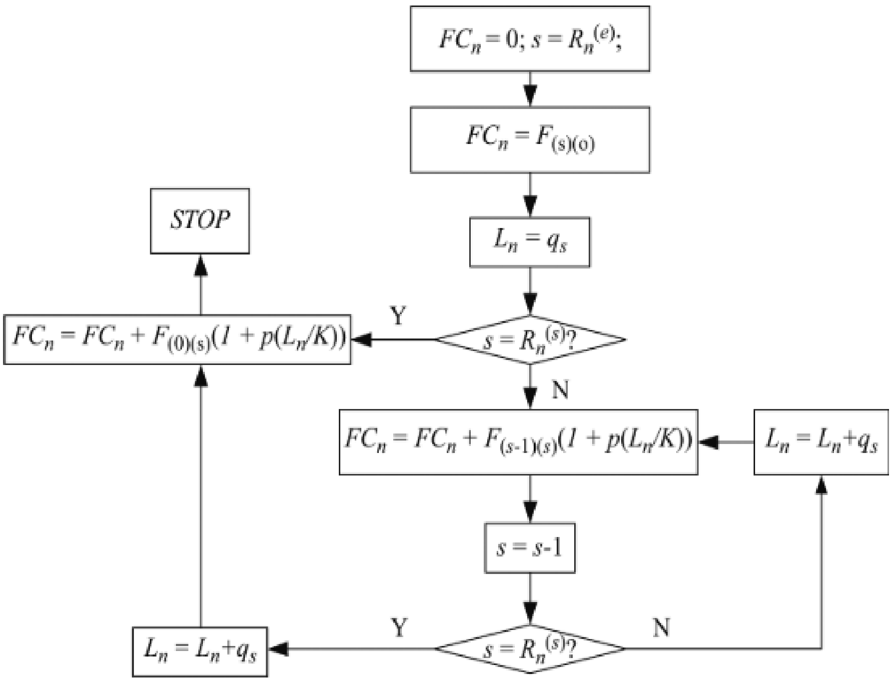

Fig. 3. Fuel Calculation Procedure

2.2.2 Update inertia weight, cognitive acceleration, dan social acceleration

One of the factors that affect an algorithm's performance in solving an optimization problem is determining the right combination of parameters. The particle size used refers to Eberhart and Yuhui [34], namely 30-50 particles.

The value of inertia weight (ω) and the coefficient acceleration (c_1 and c_2) referred to Ratnaweera, et al. [35]. The value of $\omega_{max} = 0{,}9$, $\omega_{min} = 0{,}4$, $c_{1max} = 0.5, c_{1min} = 2.5$, $c_{2min} = 0.5$, $c_{2max} = 2.5$. Furthermore, the initial velocity of each particle was assumed to be $v_0 = 0$. The maximum particle velocity was $v_{max} = 20$. Ratnaweera, et al. [35] have suggested this method carried out with a factor inertia weight (ω) (equation 9) and coefficient acceleration (c_1 and c_2) (equation 10 dan 11) which varies with time.

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$$\omega_{curr\_iter} = (\omega_{max} - \omega_{min}) * \frac{\max\_iter - curr\_iter}{\max\_iter} + \omega_{min} \quad (9)$$

$$c_1 = (c_{1max} - c_{1min}) * \frac{curr\_iter}{\max\_iter} + c_{1min} \quad (10)$$

$$c_2 = (c_{2max} - c_{2min}) * \frac{curr\_iter}{\max\_iter} + c_{2min} \quad (11)$$

2.2.3 Update velocity, particle position

Each particle was assumed to have two characteristics; position and velocity. Each particle moves in a certain space and remembers the best position ever traveled or found against a food source or objective function value. Each particle conveys information or its good position to the other particles and adjusts each position and velocity.

The following is a mathematical formulation that describes the position and velocity of particles in a search space.

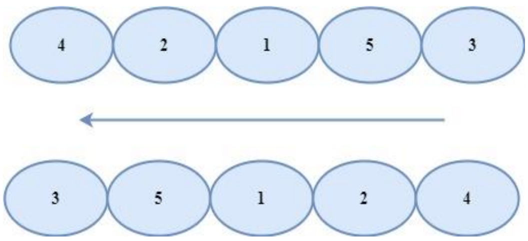
$$v_{i(t+1)} = V_{i(t)} + c_1 r_1 \left(p_{best(i)} - x_{i(t)}\right) + c_2 r_2 \left(g_{best(i)} - x_{1(t)}\right) \quad (12)$$

$$x_{i(t+1)} = v_{i(t+1)} + x_{i(t)} \quad (13)$$

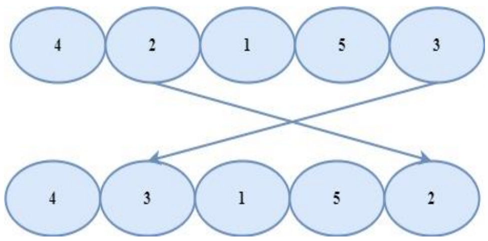
$p_{best(i)} = p_{best(i1)}, p_{best(i2)}, p_{best(i3)}, \dots, p_{best(iN)}$ represents the local best of the i(th) particle. Whereas $g_{best(i)} = g_{best(i1)}, g_{best(i2)}, g_{best(i3)}, \dots, g_{best(iN)}$ represents the global best of all particles. c_1 and c_2 are the acceleration coefficients which are positive, then r_1 and r_2 is a random number whose value is between 0 and 1.

2.2.4 Local search

To improve the PSO algorithm's performance, this study proposed PSO with the local search procedure. Some of the procedures used to maximize the efficiency of the PSO were the swap and flip procedures. Fig. 4 b illustrates the stages of the swap procedure. The swap procedure begins by selecting two positions or nodes randomly and then swapping positions. On the other hand, the flip procedure has steps where two nodes are randomly selected. Then the selected nodes are reversed in order. The stages of the flip procedure are described in Figure 4a. The implementation of the hybrid in PSO with swap and flip procedures was carried out in each iteration t as many as the number of nodes. Algorithm 1 and Algorithm 2 show the pseudocode for the PSO and HPSO algorithms.



(a)



(b)

Fig. 4. (a) flip ilustration (b) swap ilustration

To get optimal performance, Ratnaweera, et al. [35] reduce the cognitive component's value and increase the social component by changing the acceleration coefficient c1 and c2 along with the iteration. The larger the value of c1 and the smaller

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the value of c2, in the beginning, means the particles are allowed to move around the search space and move towards the best population. On the other hand, the small cognitive component's value and the large social component allow the particles to converge towards global optima at the end of the optimization.

Algorithm 1: Pseudocode Particle Swarm Optimization (PSO)

```
Algoritma PSO
Initialization
Select the variant of the PSO algorithm
Select parameters of the PSO (w1, c1max, c1min , c2max, c1min, vmax, n, max iteration (t))
Initialize the routes with a random way [position=rand.* (ub − lb) + lb]
Convert particle' position in continuous form
Initialize the position and velocity of each particle
Convert particle' position into routing division (section 2.2.2)
Calculate the initial fitness function of each particle in section 2.4.1 and eq (11)
while (t < tmax)
    do for each particle
        for each task
      do calculate the particle's fitness value according to equation (11)
            do if fitness value < Pbest
                then Pbest= fitness
            end if
            do if fitness value < Gbest
                then Gbest= fitness
            end if
            do updating inertia weight according to equation (9)
            do updating cognitive acceleration c1 according to equation (10)
            do update the social acceleration c2 according to equation (11)
            do update the particle's velocity according to the equation (12)
            do update the particle's position according to the equation (13)
        end for
    end for
end while
```

2.3 Data Collection and Experiment

2.3.1 Data Collection

In this study, several numbers nodes were used as a numerical experiment. The coordinates of customer position, number of customer requests, and capacity were based on the problems of Gaskell [36] and Dantzig and Ramser [37]. Nodes 21 and 22 were taken from Gaskell's data set [36], and node 12 was derived from the Dantzig and Ramser problem [37]. The distance between customers and the distance from the depot to the customer ($d_{(R_r^n)(R_r^{n+1})}$) were calculated by the euclidian distance formula in equation (14).

$$d_{(R_r^n)(R_r^{n+1})} = \sqrt{(X_n - X_{n+1})^2 + (Y_n - Y_{n+1})^2} \tag{14}$$

Algorithm 2: Pseudocode Hybrid Particle Swarm Optimization (HPSO)

```
Algoritma HPSO
Initialization
Select the variant of the PSO algorithm
Select parameters of the PSO (w1, c1max, c1min , c2max, c1min, vmax, n , max iteration (t))
Initialize the routes with a random way [position=rand.* (ub − lb) + lb]
Convert particle' position in continuous form
Initialize the position and velocity of each particle
Convert particle' position into routing division (section 2.2.2)
Calculate the initial fitness function of each particle in section 2.4.1 and eq (11)
while (t < tmax)
    do for each particle
          for each task
        do calculate the particle's fitness value according to equation (11)
            do if fitness value < Pbest
                then Pbest= fitness
            end if
            do if fitness value < Gbest
                then Gbest= fitness
            end if
            do updating inertia weight according to equation (9)
            do updating cognitive acceleration c1 according to equation (10)
            do update the social acceleration c2 according to equation (11)
            do update the particle's velocity according to the equation (12)
            do update the particle's position according to the equation (13)
          end for
    end for
    Apply local search
    For i = 1; node
        Perform swap on the X*. Ensure No. repeated swap in the X*
            If Xt < X*
            X* < Xt
            end if
    end for
    For j = 1 ; node
    Perform flips on the X*. Ensure No. repeated flip in the X*
            If Xt < X*
            X* < Xt
            end if
    end for
end while
```

Here, r-th was the route consisting of node s to node s + 1. KPL calculation or distance per unit of fuel refers to Kuo's research [19]. The increase in fuel consumption (ρ) at each additional load per 100 pounds or 45.35 kilograms was 2%. This study was conducted in 9 variations; three variations in the number of nodes and three variations in

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the value of the vehicle KPL. Table 1 shows the distance matrix from node 12, while Table 2 and Table 3 show the position coordinates of nodes 21 and 22.

Table 1. The distance matrix from 12 node

Node	0	1	2	3	4	5	6	7	8	9	10	11	12	demand
0	0	9	14	21	23	22	25	32	36	38	42	50	52	1200
1	9	0	5	12	22	21	24	31	35	37	41	49	51	1700
2	14	5	0	7	17	16	23	26	30	36	36	44	51	1500
3	21	12	7	0	10	21	30	27	37	43	31	37	39	1400
4	23	22	17	10	0	19	28	25	35	41	29	31	29	1700
5	22	21	16	21	19	0	9	10	16	22	20	28	30	1400
6	25	24	23	30	28	9	0	7	11	13	17	25	27	1200
7	32	31	26	27	25	10	7	0	10	16	10	18	20	1200
8	36	35	30	37	35	16	11	10	0	6	6	14	16	1900
9	38	37	36	43	41	22	13	16	6	0	12	12	20	1800
10	42	41	36	31	29	20	17	10	6	12	0	8	10	1600
11	50	49	44	37	31	28	25	18	14	12	8	0	10	1700
12	52	51	51	39	29	30	27	20	16	20	10	10	0	1100
Capacity	6000													

Table 2. The coordinates of the position of 21 node problem

No	x	y	Demand
0	145	215	0
1	151	264	1100
2	159	261	700
3	130	254	800
4	128	252	1400
5	163	247	2100
6	146	246	400
7	161	242	800
8	142	239	100
9	163	236	500
10	148	232	600
11	128	231	1200
12	156	217	1300
13	129	214	1300
14	146	208	300
15	164	208	900
16	141	206	2100
17	147	193	1000
18	164	193	900
19	129	189	2500
20	155	185	1800
21	139	182	700
Capaity	6000		

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Table 3. Coordinates of the position of 22 node problem

node	x	y	demand
0	266	235	0
1	295	272	125
2	301	258	84
3	309	260	60
4	217	274	500
5	218	278	300
6	282	267	175
7	242	249	350
8	230	262	150
9	249	268	1100
10	256	267	4100
11	265	257	225
12	267	242	300
13	259	265	250
14	315	233	500
15	329	252	150
16	318	252	100
17	329	224	250
18	267	213	120
19	275	192	600
20	303	201	500
21	208	217	175
22	326	181	75
Capacity	4500		

2.3.2 Setup the experiment

In this study, an experiment was conducted to determine the vehicle's fuel consumption's HPSO parameters' performance. The calculation experiment was carried out with variations in the number of populations and iterations. Variations in population parameters used were 30, 40, and 50 populations. Meanwhile, the iteration parameters used in the experiment varied with a range of 10-300 iterations. The calculation experiment was carried out in as many as 54 experiments. Each calculation result was performed a recapitulation of the fuel consumption results. The recapitulation of the overall experimental results was analyzed to determine population variations and iterations on numerical experiments with variations in the number of nodes.

In this study, an analysis of the Kilometers Per Liter (KPL) effect on fuel consumption was also conducted. KPL was tested with a value of 9.35, 12.8, and 16.25. Each experimental result was recorded and analyzed for the effect of the changes on the fuel consumption result. All calculation experiments were carried out using Matlab 2014a software on Windows 10 AMD A12 with x64-64 8GB RAM processor.

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3. Results and Discussion

3.1 Solution Using HPSO

In this section, the results of the experimental calculation of the FCVRP study using the Hybrid Particle Swarm Optimization (HPSO) approach were explained. The fuel consumption calculation was carried out in 3 different cases. Table 4, Table 5, and Table 6 portray the experiment calculation results with variations in the number of nodes, population, and iteration.

Table 4. Fuel consumption (liter) from 12 node

Population	Iteration					
	10	30	50	100	200	300
30	35.08	34.7578	32.6578	34.62	34.408	31.758
40	34.433	33.1703	33.3578	33.986	33.592	34.014
50	36.883	34.9766	33.2734	32.658	31.758	31.758

Table 5. Fuel consumption (liter) from 21 node

Population	Iteration					
	10	30	50	100	200	300
30	67.988	67.11	65.617	57.3616	54.463	51.05
40	68.259	59.294	56.306	54.2321	54.271	50.723
50	56.306	54.2321	54.271	50.723	50.894	48.2741

Table 6. Fuel consumption (liter) from 22 node

Population	Iteration					
	10	30	50	100	200	300
30	99.164	99.164	99.164	99.164	99.164	73.248
40	99.164	99.164	99.164	99.164	99.164	99.164
50	115.7	84.664	74.560	99.164	99.164	62.329

Table 4, Table 5, and Table 6 indicate that the optimal fuel consumption in the case of node 12 was obtained in an experiment with a population of 50 iterations of 300. Like node 12, the optimal fuel consumption in nodes 21 and 22 was obtained during the experiment on population 50 and iterations 300. Based on Table 6, it is concluded that the optimal fuel consumption tends to be obtained in experiments with large population parameters and iterations. The greater the population parameter and the iteration, the greater the probability of getting optimal fuel consumption. Therefore, to minimize fuel consumption in this FCVRP case study, it is highly recommended to use various high parameters. Population parameters and high iterations appear to be more effective in generating minimum fuel consumption.

3.2 Analysis of the Effect of Changes in KPL on Fuel Consumption

The analysis was carried out on changes in the KPL variable on the fuel consumption. The procedure used was to experiment with calculating the KPL value, which varies from 9.35 to 16.25 liters. This process functioned to find the effect of changes in the value of the KPL variable on fuel consumption value. Fig. 5 shows that the greater

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the KPL variable's value, the smaller the total fuel consumption produced. On the other hand, the total fuel consumption was observed to get more significant when the KPL value gets smaller.

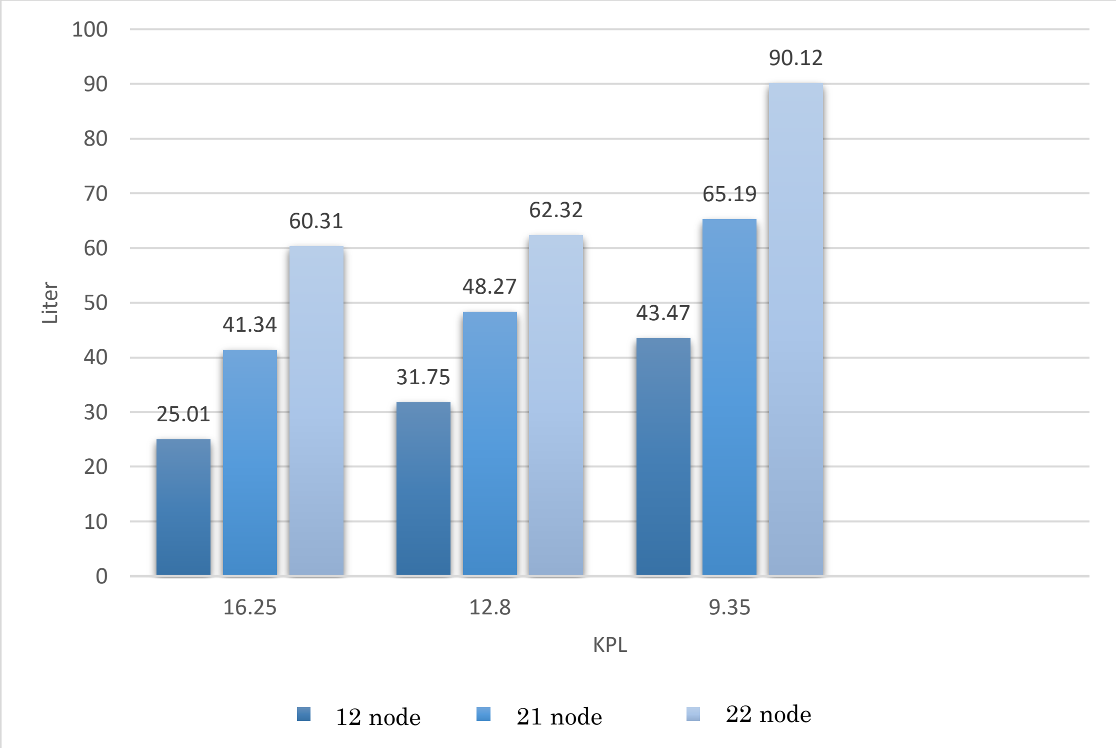

Fig. 5. Graph Analysis of the Effect of Changes in KPL variables on Fuel Consumption (FC)

4. Conclusion

This study discussed the problem of the Fuel Consumption Vehicle Routing Problem (FCVRP). The Hybrid Particle Swarm Optimization (HPSO) algorithm was developed to minimize fuel consumption in transportation activities. The experiment showed that to obtain a more optimal fuel consumption, the population and iteration parameters need to be increased. The effect of changes in KPL on energy consumption was also investigated. The results indicated that the greater the KPL variable's value, the smaller the total fuel consumption produced. Some of the limitations of this study included not considering the pick-up load at each node. The suggestion for further research is to investigate FCVRP problems by considering the pick-up and delivery load.

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