Completion of FCVRP using Hybrid Particle Swarm Optimization Algorithm

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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...
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 flyfire 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 Nadaraj [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 gap, 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:

- \textbf{KPL} : distance traveled per unit of fuel
- \textbf{p} : fuel consumption increases with each additional load
- \textbf{k} : increase in load capacity
- \textbf{L}_{ij} : load
- \textbf{K} : collection of vehicles at the depot, with \textbf{K} = \{1,2,..,k\}
- \textbf{R}^{k} : set of routes traveled by the vehicle \textbf{k}, with \textbf{R} = \{R^{1},R^{2},..,R^{k}\}
- \textbf{V} : set node
- \textbf{d}_{ij} : distance from \textbf{i} to \textbf{j} nodes
- \textbf{r} : route index
- \textbf{C}_{r}^{k} : operational costs for vehicle \textbf{k} traveling the route \textbf{r}
- \textbf{A}_{ri}^{k} : constant, value 1 if vehicle \textbf{k} with route \textbf{r} to customer \textbf{i} and value 0 for other conditions
- \textbf{T}^{k} : time taken for the vehicle to travel the route \textbf{r}
- \textbf{T}_{max} : maximum allowable travel time

\textbf{FC} : Total Fuel Consumption

\textbf{R}_{r}^{k} : s\textbf{th node in} \textbf{r}th route, for example \textbf{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:

\[
\text{Minimize } FC = \sum_{\text{v} \in V} \sum_{\text{r} \in R^{v}} \frac{d_{ij}}{KPL_{ij}} \left(1 + p(L_{ij}/k)\right)^{k} x_{r}^{v} \tag{1}
\]

Constraint:

\[
\sum_{k \in K} \sum_{\text{r} \in R^{k}} C_{r}^{k} x_{r}^{k} \geq 1 \quad \forall \ i \in N \tag{2}
\]

\[
\sum_{k=1}^{K} y_{ik} = 1 \quad \forall \ i \in V \{0\} \tag{3}
\]

\[
\sum_{k=1}^{K} y_{0k} = K \tag{4}
\]

\[
\sum_{\text{v} \in \text{V}} d_{ij} y_{ik} \leq C_{k} \quad \forall k = 1,2,..K \tag{5}
\]

\[
\sum_{k \in K} x_{r}^{k} \geq 1 \quad \forall \ k \in K \tag{6}
\]

\[
\sum_{\text{r} \in R^{k}} T_{r}^{k} x_{r}^{k} \leq T_{\text{max}} \quad \forall \ k \in K \tag{7}
\]

\[
x_{r}^{k} \in \{0,1\} \quad \forall \ k \in K, \ \forall \ r \in R^{k} \tag{8}
\]

With the decision variables:

\[
x_{r}^{k} = \begin{cases} 
1, & \text{If } \text{ vehicle } k \text{ using } r \text{ route} \\
0, & \text{Other}
\end{cases}
\]
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 $\chi^*$ 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.

\[
P = \begin{pmatrix}
0.56 & 0.91 & 0.85 \\
0.77 & 0.39 & 0.75 \\
0.42 & 0.12 & 0.55
\end{pmatrix}
\]

(a)

\[
P = \begin{pmatrix}
0.56 & 0.91 & 0.85 \\
0.77 & 0.91 & 0.75 \\
0.42 & 0.12 & 0.55
\end{pmatrix}
\]

(b)

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

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 ($\omega$) and the coefficient acceleration ($c_1$ and $c_2$) referred to Ratnaweera, et al. [35]. The value of $\omega_{\text{max}} = 0.9$, $\omega_{\text{min}} = 0.4$, $c_{1\text{max}} = 0.5$, $c_{1\text{min}} = 2.5$, $c_{2\text{min}} = 0.5$, $c_{2\text{max}} = 2.5$. Furthermore, the initial velocity of each particle was assumed to be $v_0 = 0$. The maximum particle velocity was $v_{\text{max}} = 20$. Ratnaweera, et al. [35] have suggested this method carried out with a factor inertia weight ($\omega$) (equation 9) and coefficient acceleration ($c_1$ and $c_2$) (equation 10 dan 11) which varies with time.
\[ \omega_{\text{curr} \text{ iter}} = (\omega_{\text{max}} - \omega_{\text{min}}) \cdot \frac{\text{max } \text{ iter} - \text{curr } \text{ iter}}{\text{max } \text{ iter}} + \omega_{\text{min}} \]  
\[ c_1 = (c_{1\text{max}} - c_{1\text{min}}) \cdot \frac{\text{curr } \text{ iter}}{\text{max } \text{ iter}} + c_{1\text{min}} \]  
\[ c_2 = (c_{2\text{max}} - c_{2\text{min}}) \cdot \frac{\text{curr } \text{ iter}}{\text{max } \text{ iter}} + c_{2\text{min}} \]  

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.

\[ v_{i(t+1)} = v_{i(t)} + c_1 r_1 (p_{\text{best}(i)} - x_{i(t)}) + c_2 r_2 (g_{\text{best}} - x_{i(t)}) \]  
\[ x_{i(t+1)} = v_{i(t+1)} + x_{i(t)} \]  

\( p_{\text{best}(i)} = p_{\text{best}(i1)}, p_{\text{best}(i2)}, p_{\text{best}(i3)}, \ldots, p_{\text{best}(IN)} \) represents the local best of the i(th) particle. Whereas \( g_{\text{best}} = g_{\text{best}(i1)}, g_{\text{best}(i2)}, g_{\text{best}(i3)}, \ldots, g_{\text{best}(IN)} \) 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 as many as the number of nodes. Algorithm 1 and Algorithm 2 show the pseudocode for the PSO and HPSO algorithms.

To get optimal performance, Ratnaweera, et al. [35] reduce the cognitive component's value and increase the social component by changing the acceleration coefficient \( c_1 \) and \( c_2 \) along with the iteration. The larger the value of \( c_1 \) and the smaller
the value of \( c_2 \), 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)

```
Algorithm PSO
Initialization
Select the variant of the PSO algorithm
Select parameters of the PSO \((w_1, c_{1\text{max}}, c_{1\text{min}}, c_{2\text{max}}, c_{2\text{min}}, v_{\text{max}}, n, \text{max iteration} (t))\)
Initialize the routes with a random way \([\text{position}=\text{rand}. \times (\text{ub} - \text{lb}) + \text{lb}]\)
Convert particle's position in continuous form
Initialize the position and velocity of each particle
Convert particle's 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 \((t < t_{\text{max}})\)
    do for each particle
        do for each task
            do calculate the particle’s fitness value according to equation (11)
                do if fitness value < \( P_{\text{best}} \)
                    then \( P_{\text{best}} = \text{fitness} \)
                    end if
                do if fitness value < \( G_{\text{best}} \)
                    then \( G_{\text{best}} = \text{fitness} \)
                    end if
                do updating inertia weight according to equation (9)
                do updating cognitive acceleration \( c_1 \) according to equation (10)
                do update the social acceleration \( c_2 \) 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 \( d_{(R^n_i)(R^{n+1}_j)} \) were calculated by the euclidian distance formula in equation (14).

\[
d_{(R^n_i)(R^{n+1}_j)} = \sqrt{(X_i - X_{n+1})^2 + (Y_i - Y_{n+1})^2}
\]  

(14)
Algorithm 2: Pseudocode Hybrid Particle Swarm Optimization (HPSO)

Algorithm HPSO

Initialization
Select the variant of the PSO algorithm
Select parameters of the PSO ($w$, $c_{1\text{max}}$, $c_{1\text{min}}$, $c_{2\text{max}}$, $c_{2\text{min}}$, $v_{\text{max}}$, $n$, max iteration ($t$))
Initialize particle’s position in continuous form
Convert position and velocity of each particle
Convert particle’s 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 ($t < t_{\text{max}}$)
   do for each particle
      for each task
         do calculate the particle’s fitness value according to equation (11)
            do if fitness value $< P_{\text{best}}$
               then $P_{\text{best}} = \text{fitness}$
            end if
            do if fitness value $< G_{\text{best}}$
               then $G_{\text{best}} = \text{fitness}$
            end if
            do updating inertia weight according to equation (9)
            do updating cognitive acceleration $c_1$ according to equation (10)
            do update the social acceleration $c_2$ 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 $X^\ast$. Ensure No. repeated swap in the $X^\ast$
      If $X_t < X^\ast$
      $X^\ast < X_t$
   end if
   For $j = 1$; node
      Perform flips on the $X^\ast$. Ensure No. repeated flip in the $X^\ast$
      If $X_t < X^\ast$
      $X^\ast < X_t$
   end if
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 ($\rho$) 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
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 node 12

| 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 | 44 | 51 | 52 | 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  | 7  | 11 | 13 | 17 | 25 | 27 | 21 | 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 node 21 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     |

Capacity 6000
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 | 125    |
| 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.
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
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.

![Graph Analysis of the Effect of Changes in KPL variables on Fuel Consumption (FC)](image)

**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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