Research Article

Particle Swarm Optimization Algorithm to Solve Vehicle Routing Problem with Fuel Consumption Minimization

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ABSTRACT

The Conventional Vehicle Routing Problem (VRP) has the objective function of minimizing the total vehicles' traveling distance. Since the fuel cost is a relatively high component of transportation costs, in this study, the objective function of VRP has been extended by considering fuel consumption minimization in the situation wherein the loading weight and traveling time are restricted. Based on these assumptions, we proposed to extend the route division procedure proposed by Kuo and Wang [4] such that when one of the restrictions can not be met, the routing division continues to create a new sub-route to find an acceptable solution. To solve the formulated problem, the Particle Swarm Optimization (PSO) algorithm is proposed to optimize the vehicle routing plan. The proposed methodology is validated by solving the problem taking a particular day data from a bottled drinking water distribution company. It was revealed that the saving of at best 13% can be obtained from the actual routes applied by the company.

INTRODUCTION

The large use of fossil fuels in transportation activities affects the carbon emission (CO_2) which is a well-known as greenhouse gas (GHG), and it accounts for about three-quarters of total emissions [1]. Scientists and meteorologists state that the increase in greenhouse gas in the atmosphere is the foremost cause of global warming and has become a serious problem for the environment [2]. According to Ponthalir and Nadarajan [3], vehicle fuel consumption is one of the important parameters in GHG. Therefore, reducing vehicle fuel consumption is a suitable policy for organizations involved in logistics transportation. The amount of vehicle fuel consumption is affected by the weight of the load. US Department of Energy [4] states that for every 100-pound payload addition, fuel consumption increases by 2%. Consequently, fuel consumption is an important study in logistics and transportation [5]. The transportation field held the second highest contributor to greenhouse gases, where it was accountable for 23% of the global 〚CO〛_2 emissions in 2014 [1] Freight transportation acts as an essential role in economic development but dangerous to the environment. Most of the freight transportation is carried out by trucks run on diesel engines, which are the major source of CO_2 emissions [6]. Therefore, minimizing fuel consumption can directly reduce carbon emissions. Based on the description, logistics and

transportation companies require a model to accomplish the vehicle routing problem to reduce fuel consumption.

The Vehicle Routing Problem (VRP) is an optimization problem that is applied in various fields. VRP is usually used to solve transportation, logistics, and scheduling problems [7-9]. The earliest VRP study solved the routing plan of trucks from a bulk terminal to a large number of service stations [10]. The classification of VRPs has developed vastly in many literatures. VRP is classified into several types based on its objective and the proposed constraints [11]. For instance, Pickup and Delivery VRP sets a route considering goods pickup and delivery [12-15]. Capacitated VRP (CVRP) considers the loading weight that can be carried by the vehicle [16-19]. Consequently, CVRP forms several sub-routes [20]. VRP With Time Windows (VRPTW) includes customer service time that occurs within a specified time windows [21-25]. In the VRP concept, the fuel consumption cost in distributing products depends on several variables, including vehicle load, fuel consumption per unit distance, fuel price, inflation of tires, and total distance travelled [4]. In common, VRP studies are more about decreasing travel distances and travel times. Meanwhile, there are only a few studies of VRP to minimize fuel consumption. [4].

According to the US Department of Energy [26], one of the factors that affect the amount of fuel consumption of vehicles is

the weight of the load. Based on these conditions, vehicle fuel consumption does not only depend on the mileage. Therefore, these factors can be formulated as a model to solve vehicle route problems. Eglese and Bektas [27] stated that the amount of CO_2 emitted by a vehicle comes from the amount of fuel consumption. Kuo [28] and Xiao [1] applied a simulated annealing algorithm to solve VRP with fuel consumption. The study considers time-dependent travel speed and fuel consumption rate (FCR) for reducing fuel consumption. The time-dependent travel speed factor is also presented in research [29-32]. The methods that are used are the Djikstra algorithm and dynamic programming heuristic, ant colony algorithm, tabu search algorithm, and particle swarm algorithm. Also, Montoya [33] determined vehicle routes by considering alternative fuel vehicles (AFVs) to reduce fuel consumption and emissions. In another study, Montoya [2] used a multi-space sampling heuristic. Kuo and Wang [4] conducted a study on the effect of load weight on fuel consumption using the tabu search algorithm.

There are several studies on VRP using the particle swarm optimization algorithm [3, 32, 34-40]. Poonthalir and Nadarajan [3] involved the varying speed of the vehicle based on the triangular distribution model into their mathematical model. The completion of the proposed model by the PSO algorithm results in a better route with minimum fuel consumption under varying speed settings. Then a proposed model was conducted by Norouzi [32] to solve the time-dependent vehicle routing problem (TDVRP). The result showed that the TDVRP model with the PSO algorithm was able to reduce carbon emission. Tavakoli [34] conducted a model to solve the capacitated vehicle routing problem (CVRP) and obtained minimum cost on satisfying customer demand. The particle swarm optimization algorithm also solved the vehicle routing problem with simultaneous pickup and delivery (VRPSPD) which was arranged by Goksal [35]. Ai and Kachitvichyanukul [37] also researched VRPSD using the PSO algorithm. Their method was successfully reduced the number of vehicles that served the customers. The study utilized several algorithms for comparison. The results showed that the PSO algorithm is more efficient than others. MirHassani [39] developed the PSO algorithm to solve the open vehicle routing problem (OVRP). The study presented PSO can produce various solutions and sustained the best solution found through the iteration process. A proposed model was conducted by Hannan [40] to determine a routing plan in CVRP as a tool for waste collection and route optimization. Zhao [41] investigated the performance of the particle swarm optimization algorithm for the vehicle routing problem with time windows.

PSO has become a popular global optimization with most problems that can be solved well where the variables are real numbers [42]. Particle Swarm Optimization is widely used due to the number of advantages that the method has. PSO can be applied to scientific and technical research, robustness, and merely has calculation when compared with mathematical algorithm and other heuristic optimization techniques [43]. The PSO algorithm is suitable for solving the vehicle routing problem with difficult combinatorial optimization problems and short computation time. In the Vehicle Routing Problem, Marinakis [44] stated that the PSO algorithm stands the fifth position among 39 other algorithms and takes the first position among nature-inspired algorithms through tests on a set of benchmark instances.

According to the description above, the PSO algorithm works properly in solving vehicle routing problem issues. The simplicity of the algorithm and its good performance has made PSO draws a lot of attention among researchers and has been applied in various optimization problems.

Kuo and Wang [4] presented a model to calculate the total fuel consumption given a vehicle routing plan. They proposed a Tabu Search (TS) for optimizing the vehicle routing plan. In their research, they assumed the total loading weight of a vehicle is limited. Therefore, the sum of the customer's requested weight in a sub-route cannot exceed the vehicle capacity. Thus, the route is divided into several sub-routes. After forming a sub-route, total fuel consumption was calculated.

To the best of our knowledge, the distribution activities by vehicles usually work within a certain period. We add one more assumption that the total traveling time of a vehicle is limited. Thus, dividing the route into several sub-routes is based on those two limitations. If one of the limitations cannot be met, then the routing division continues to create new sub-route. By adding these limitations, we modified the route division procedure proposed by Kuo and Wang [4]. We also change the metaheuristic algorithm used from Tabu Search to Particle Swarm Optimization in order to improve vehicle routing plan optimization. This research is also implemented to solve real life problem of bottled drinking water distribution in Lombok island.

METHOD

Total Fuel Consumption Calculation

Kuo and Wang [4] proposed a model for calculating fuel consumption based on previously known vehicle routes. They stated that fuel consumption is affected by the distance of transportation, transportation speed, and loading weight. The vehicle speed is classified into three levels: high speed, medium speed, and low speed [4]. In their paper, MPG (miles per gallon) is used to show how far your car can travel for every gallon (or 4.55 liters) of fuel it uses. Furthermore, the MPG for each vehicle traveling from customer i to customer j with one of the speed levels can be estimated using the fuel consumption guide by the US Department of Energy [45]. When the MPG_{ij} and distance d_{ij} within customer i and j are known, the fuel consumption F_{ij} for an empty vehicle leaving from customer i to j can be calculated by equation (1).

$$F_{ij} = d_{ij}/MPG_{ij} \qquad (1)$$

In addition, the amount of loading weight will increase fuel consumption by p percent due to additional k pounds. When the vehicle transports goods weighing L from customer i to j, then, the total fuel consumption is computed as

$$FC_{ij} = \frac{d_{ij}}{MPG_{ij}}\left(1 + p\left(L_{ij}/k\right)\right) \qquad (2)$$

Thus, for the nth sub-route, if the sequence starts from customer $R_n^{(s)}$ and ends at customer $R_n^{(e)}$, and the weight of the order from the retail store s is q_s, the total fuel consumption (FC_n) can be calculated by the procedure as shown in Figure 1, where $F_{(s)(0)}$ is fuel consumption of empty vehicle from customer s to depot, $F_{(0)(s)}$ is fuel consumption of empty vehicle from depot to customer s, and L_n is the current load weight of nth sub-route.
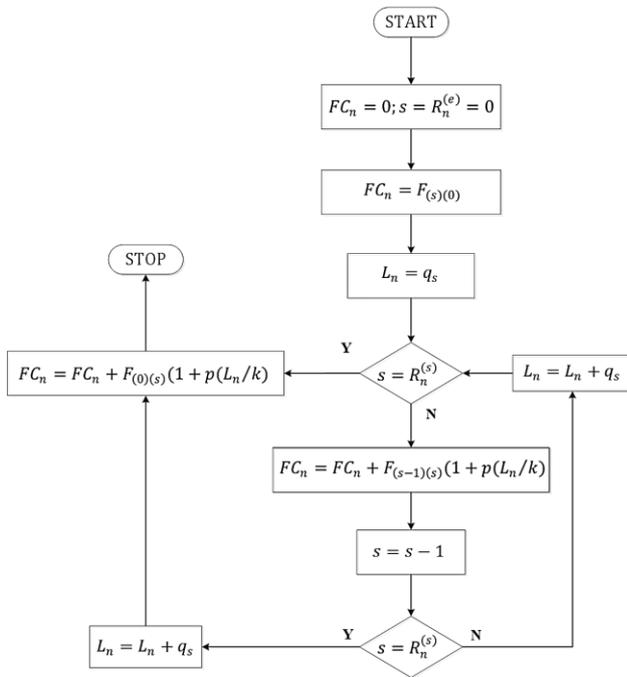
Figure 1. Total Fuel Consumption Calculation Procedure
(Source: Kuo and Wang [4])

The total fuel consumption model initiated by Kuo and Wang [4] is arranged by reversing the order of the formed sub-routes. Figure 1 illustrates the sum of all customer requests distributed from customer $R_n^{(e)}$ and followed by the next customer in reverse order to customer $R_n^{(s)}$, and finally ends at the distribution center.

Routing Division and Fuel Consumption

A vehicle routing plan refers to a sequence of all customers. The sequence can be divided into several sub-sequences (or sub-routes). A sub-sequence is the route of a vehicle that starts from the distribution center and then visits some of the all existing customers, and finally returns to the distribution center. Kuo and Wang [4] assumes that the total loading weight must not exceed the vehicle capacity. If a routing plan for all customers is given, a customer's request will be assigned to the next sub-route.

A side of load capacity, the vehicle typically has a maximum traveling time (T_{max}). Therefore, the proposed research includes T_{max} as additional consideration in the routing division procedure. If the vehicle's total traveling time T exceeds T_{max}, then the customer will be assigned to the next sub-route, hence, extending the routing division procedure proposed by Kuo and Wang [4]. The results of our proposed routing division procedure are shown in Figure 2.

Starting with index for sub-routes $n = 1$, we assign an a sequence of customers $s = 1$, and total loading weight of a vehicle $Q = 0$, maximum traveling time of a vehicle $T = 0$, and total vehicle fuel consumption on a routing plan $TF = 0$. Using the PSO algorithm (explained later), we determine the customer at the start of 1st sub-route $(R_1^{(s)}) = 1$. Based on the input of customer demand and travel time data, the q_s and t_s values are recorded, and the Q and T value are updated by q_s and t_s, respectively. If Q less than vehicle load capacity C or T less than T_{max}, then the customer is feasible to enter 1st sub-route. This iterative procedure continues by adding the next customer i.e., updating $s = s + 1$ as long as C
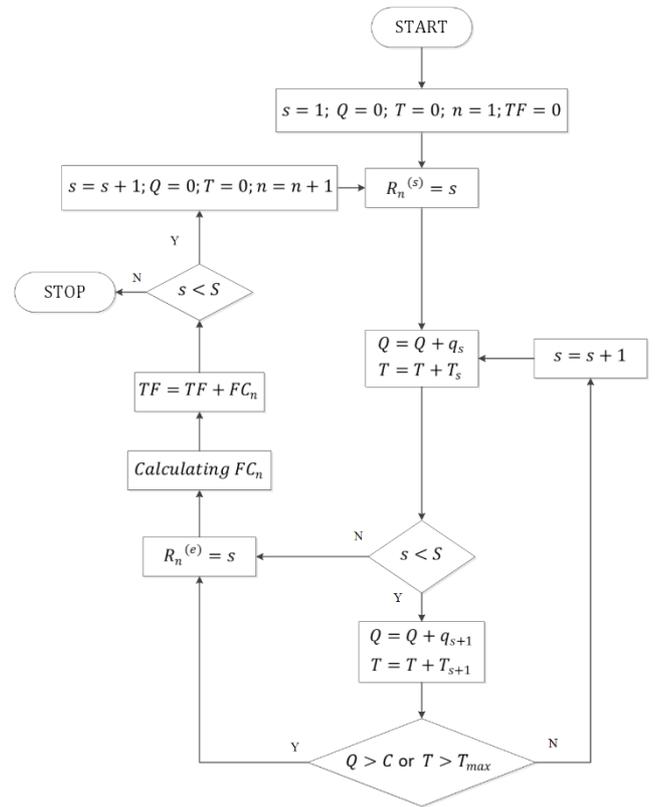

Figure 2. Proposed Routing Division and Fuel Consumption Procedure

and T_{max} are still met and/or the total number of customers has been assinged ($s = S$). Keep in mind that the sub-route start and end is at the distribution center.

If the addition of customers in 1st sub-route causes $Q > C$ or $T > T_{max}$ then the procedure for adding customers is stopped and set the end of 1st sub-route $(R_n^{(s)}) = s$. The total fuel consumption on 1st sub-route, FC_1, are then computed TF is updated by adding FC_1. Finaly, if $s = S$ then the routing division procedure and the total fuel consumption computation have been completed. Otherwise, the iteration continues by setting up $s = s + 1$, $n = n + 1$, $Q = 0$, $T = 0$. The assignment the customer is carried out to be the beginning of the $(n + 1)th$ sub-route to obtain $(R_{n+1}^{(s)}) = s+1$.

Particle Swarm Optimization Algorithm

Particle Swarm Optimization (PSO) is an optimization technique that mimics the behavior of fish schooling or birds flocking [46]. The PSO algorithm contains a set of particles. Each particle has a possible solution that is initialized by a population of random candidate solutions [47]. Each particle has a velocity and position. The particles move at random velocities and iteratively moving through the solution space. In the N-dimensional space, each particle has an initial velocity and moves through the solution space. Then the velocity of the particles is evaluated to get to the best position in a swarm. Each particle will remember its best position so far. The current particle's best position is called p_{best} and the best move of all particles in all over iteration, known as global best g_{best}. According to Santosa [48], the velocity of the ith particle of the search space is updated as

$$v_{i(t+1)} = V_{i(t)} + c_1 r_1 \left(p_{best(i)} - x_{i(t)} \right) + c_2 r_2 \left(g_{best(i)} - x_{1(t)} \right) \quad (3)$$

where t is the current iteration, $p_{best(i)}$ represents particle i's local best. Moreover, $g_{best(i)}$ denotes particle i's the global best position. Coefficient c_1 and c_2 are used to develop the individual and social achievement of the particle. Then, r_1 dan r_2 are random numbers specified in the interval $[0, 1]$. Equation (3) is employed to calculate the current particle velocity based on its previous velocity. Then the particles move toward a new position according to equation (4). If the p_{best} value is lower than the global best value (g_{best}), then the local best solution replaces the global best solution.

$$x_{i(t+1)} = v_{i(t+1)} + x_{i(t)} \qquad (4)$$

One of the factors that affect the performance of an algorithm in solving optimization problems is the determination of the right parameters. Eberhart & Kennedy [49] explain that if c_1 is relatively greater than the social component c_2, it leads the particle to exceed the limit of the search space. On contrary, if the value of c_2 is greater than c_1, particles will find a premature position before going to local optimal. Since exploitation and exploration are expected to be balanced to optimize multi-objective optimization, Ratnaweera [47] introduced the time-varying acceleration coefficient as an approach for determining parameters in the PSO. Therefore, in this research, the time-variant acceleration coefficient (c_1 and c_2) and the inertia coefficient (ω) are used for the cognitive and social acceleration during iteration. The aim of developing this parameter is to increase the global search at the earliest optimization time and to encourage the particles to meet the global optima at the end of the search. The mathematical representation of this concept is given by equation (5), (6) and (7), respectively.

$$\omega_{curr\_iter} = (\omega_{max} - \omega_{min}) * \frac{max\_iter - curr\_iter}{max\_iter} + \omega_{min} \qquad (5)$$

$$c_1 = (c_{1max} - c_{1min}) * \frac{curr\_iter}{max\_iter} + c_{1min} \qquad (6)$$

$$c_2 = (c_{2max} - c_{2min}) * \frac{curr\_iter}{max\_iter} + c_{2min} \qquad (7)$$

where c_{1max}, c_{1min}, c_{2max} and c_{2min} are constants, $curr\_iter$ is the current iteration number and max_iter is the maximum number of permitted iterations.

Particle Swarm Optimization Pseudocode

The work process of the PSO algorithm for VRP is described as follows.

1) Determine the parameters used in this study by setting the values of w_1, c_{1max}, c_{1min}, c_{2max}, c_{2min}, population size (N), and maximum iteration (t).
2) Randomly initialize particle using the number of population and dimension. The dimension value is obtained from the number of nodes minus 1. In this study, the number of nodes represents the number of customers. After obtaining the initial position of the particles, sort the random numbers of the particle positions using the Large Rank Value (LRV) method. LRV is a method for ordering from largest to smallest. The position of the particles after being sorted will form a route of travel [50].
3) Convert the initial position of the sorted particles using the route division procedure according to Figure 2.
4) After obtaining the route, calculate the fitness function value on each route. To evaluate the fitness function, perform a procedure based on the fuel consumption calculation in equation (2) for each particle. Compare the

particle fitness value with g_{best}. If g_{best} is the most reliable, then g_{best} is updated. Otherwise, if the current value is better than g_{best}, then assign g_{best} to the value of the current particle position.
5) Calculate particle velocity usng equation (3) and update the position of the particles based on equation (4). At this stage, the value of inertia weight (ω), cognitive acceleration c_1, and social acceleration c_2 are updated based on equations (5) (6) and (7). All particles move towards the optimal point with initial velocity assumed to be zero. Then set iteration $i = 1$.
6) Check if the current solution has converged. If the positions of all the particles point to the same value, the convergent is reached. Otherwie, repeat the steps by updating the iteration.

There are several stop conditions that can be used in Particle Swarm Optimization. According to Menhas et al. [51], the PSO algorithm will stop if one of the following conditions is met: the specified maximum iteration has been reached, an accepted solution has been obtained, or there is no change in the result after several iterations. The pseudocode of the PSO algorithm is presented in Figure 3.

Algorithm

Initialization
Select parameters of the PSO (w_1, c_{1max}, c_{1min}, c_{2max}, c_{1min}, v_{max}, N , max iteration (t))
Initialize the particle position with a random way [position=$rand.* (ub - lb) + lb$]
Initialize the particle position in continuous form
Convert particle' position into routing division (procedure: figure 2
Calculate the initial fitness function of each particle (procedure: figure 1) and equation 2
while ($t < t_{max}$)
    do for each particle
        for each task
            do calculate the particle's fitness value according to equation 2
            do if fitness value $< P_{best}$
                then P_{best}= fitness
            end if
            do if fitness value $< G_{best}$
                then G_{best}= fitness
            end if
            do update inertia weight according to equation 5
            do update cognitive acceleration c_1 according to equation 6
            do update social acceleration c_2 according to equation 7
            do update the particle's velocity according to the equation 3
            do update the particle's position according to the equation 4
        end for
    end for
end while

Figure 3. Pseudocode of Particle Swarm Optimization

Table 1. Distance Matrix and Customer Demand

Customer	0	1	2	3	Demand
0	0	4	2	3	0
1	4	0	7	4	5
2	2	7	0	3	4
3	3	4	3	0	7

Table 2. Particle Position

Particle	Particle position			Route	Fitness
0	-15.097	-1.388	-9.451	3-2-1	2.379
1	-19.373	-4.069	-10.639	2-3-1	2.257
2	-7.460	-4.430	-6.847	2-3-1	2.257
3	-11.059	-4.437	-5.715	2-3-1	2.257

Table 3. Customers Demand

No	Customer ID	Demand (kg)	No	Customer ID	Demand (kg)
1	NAM	-	15	WR-ZHR	639
2	RS-NTB	797	16	KS-GYG	532
3	RSI -PH	777	17	WR-NB	688
4	APTK-I	434.5	18	APTK-C	472.5
5	WR-SD	847	19	BKS-SJ	645.5
6	ASTN	532	20	RST-K	861
7	GP-H	458.5	21	RM-TK	665
8	SNR-B	591	22	RM-PTA	703.5
9	RS-U	609	23	RM-M	591
10	WR-EC	687	24	KKDI-SB	748
11	RM-C	798	25	RM-NP	454.5
12	KPR-S	459	26	RM-NUB	558.5
13	WR-BRK	454.5	27	KTR-G	569
14	PSR-KS	628.5			

Validation

The validation is required to ensure that the MATLAB coding computation generates the same results as of the manual calculation using hypothical data of three customers. Table 1 presents numerical data of the distance matrix and demand of three customers. At the end of the process, the best solution obtained by the entire swam will be returned as the final optimum for the optimization problem which is presented in Table 2. Figure 4 presents the best particle position in MATLAB. Because the software and manual calculations are the same, all algorithmic procedures are concluded as valid.

Implementation of The Proposed VRP Model

The proposed VRP model is implemented by solving the problem taking a particular day data from bottled drinking water distribution company. The data is processed using MATLAB R2014a with the particle swarm optimization (PSO) algorithm. The result includes the proposed route and total fuel consumption. Furthermore, we compare the total fuel consumption of the initial route and the proposed route. The initial route states is the route currently used by the company.

RESULT AND DISCUSSION

Narmada Awet Muda (NAM) company is the largest distributor of bottled drinking water in Lombok Island of which one of the

```
pos =

   -15.0971   -1.3881   -9.4514
   -19.3735   -4.0691   -10.6398
    -7.4603   -4.4300   -6.8477
   -11.0590   -4.4372   -5.7156

cg_curve =

    2.2527    2.2527
```

Figure 4. MATLAB Output for the Test Problem

market region is Mataram city. There are 26 customers spread across Mataram city. The total product demand for each customer is calculated on a particular day. The process of distributing goods starts from the distribution center (DC) to the customer and then returns to DC. The distributed products consist of large bottles (19 kgs), medium bottles (15.3 kgs), small bottles (8.8 kgs), and glass (11.3 kgs). The demand for each customer is obtained by multiplying the product's weight by the number of products ordered. The list of customer demands is presented in Table 3. The vehicle departs from the depot using two homogeneous vehicles of the colt diesel engine (CDE) type with a maximum of 2.5 tons. The vehicle may return to the depot because of its limited capacity. The vehicle has an average fuel efficiency of 8 km/liter. The maximum travel time for the vehicle is 8 hours. To find out the vehicle distance traveled, a distance matrix is required, which was obtained from a distance between customers using Google Maps application. Furthermore, we got the initial route order of the vehicles from the field study.

Figure 5 presents the vehicle route in the initial condition. The initial route consists of seven sub-routes. Each sub route is described by different line colors. The number point at a customer location refers to the index number of the customer. The amount of fuel consumption on each of these sub-routes is presented in Table 4. According to Table 4, the total fuel consumption on the initial route is 50.5179 liters with a total distance of 248.8 km. The total amount of fuel consumption is the addition of fuel consumption on all sub-routes. Sub-route 1 spent 6.8059 liters of fuel to fulfill four customers. In sub-route 2, the vehicle satisfied four customers and consumed 8.0480 liters of fuel. Fuel consumption in sub-route 3 is 8.0757 liters with four trips. Sub-route 4 fulfilled four customers with total fuel consumption of 7.1465 liters. In sub-route 5, the vehicle consumed 5.5132 liters to travel to three customers. Vehicle fuel consumption on the sub-route 6 spent 8.6871 liters of fuel. The trips to the three customers in sub-route 7 consumed 6.2415 liters of fuel.
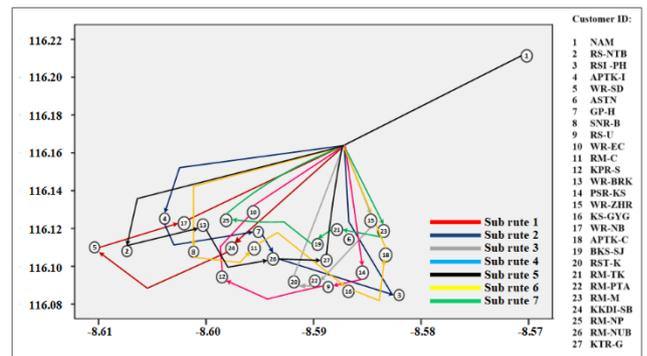

Figure 5. Initial Route

Table 4. Fuel Consumption of the Initial Route

Sub-Routes	Route-Sequence	Distance (km)	Fuel Consumption (l)
1	1-2-13-26-27-1	34.4	6.8059
2	1-8-11-18-16-1	32.1	8.048
3	1-14-9-10-12-1	36.7	8.0757
4	1-23-21-19-25-1	29.8	7.1465
5	1-15-20-22-1	37.5	5.5132
6	1-3-4-7-26-1	41.6	8.6871
7	1-24-5-17-1	36.7	6.2415
Total		248.8	50.5179

Table 5. Fuel Consumption of the Proposed Route

Sub-Routes	Route-Sequence	Distance	Fuel consumption (l)
1	1-2-9-16-1	39.2	7.8814
2	1-20-22-3-1	37.6	6.1738
3	1-6-19-26-24-1	38.7	6.1209
4	1-21-13-17-4-1	32.6	5.0212
5	1-25-5-8-18-1	39.5	7.2012
6	1-15-23-12-10-1	34.7	6.2126
7	1-11-7-27-14-1	30.6	5.4243
Total		252.9	44.0354

Table 6. Comparison of the Total Fuel Consumption

Initial Route	Proposed Route	Fuel Consumption (l)	
		Initial Routes	Proposed Routes
1-2-13-26-27-1	1-2-9-16-1	6.8059	7.8814
1-8-11-18-16-1	1-20-22-3-1	8.048	6.1738
1-14-9-10-12-1	1-6-19-26-24-1	8.0757	6.1209
1-23-21-19-25-1	1-21-13-17-4-1	7.1465	5.0212
1-15-20-22-1	1-25-5-8-18-1	5.5132	7.2012
1-3-4-7-26-1	1-15-23-12-10-1	8.6871	6.2126
1-24-5-17-1	1-11-7-27-14-1	6.2415	5.4243
Total		50.5179	44.0354
Deviation		6.5 liters	
saving		13%	

The initial routes is resolved using the proposed VRP model, and the PSO algorithm is then applied with the value of the parameters is set to ωmax = 0.9, ωmin = 0.4, c1min = 0.5, c1max = 2.5, c2min = 0.5, c2max = 2.5. The initial velocity of each particle is assumed to be equal to v0 = 0. The maximum velocity is set to vmax = 20. The value of ub and lb were defined as [-10:10]. The population size was set to 20, 30, 50, 100, 200, and 300 and the iteration maximum varies between 30 and 500.

The result yields new route-sequences for the company. The load of the vehicle is admitted to the routing division procedure (see figure 2). The route obtained from the software data processing is quite different from the initial route. The proposed route is displayed in Figure 6 and the amount of fuel consumption for each sub route is presented in Table 5. It shows that the total fuel consumption in the proposed route is 44.0354 liters with a total distance of 252.9 km. Sub-route 1 consumed 7,814 liters of fuel to satisfy three customers' demands. In sub-route 2, the vehicle visited three customers with fuel consumption of 6.1738 liters. Fuel consumption on sub-route 3 is 6.1209 liters and the vehicle traveled to four customers' locations. Total fuel consumption on sub-route 4 is 5.0212 liters and it fulfilled four customers' demand. In sub-route 5, fuel consumption is 7.2012 liters after
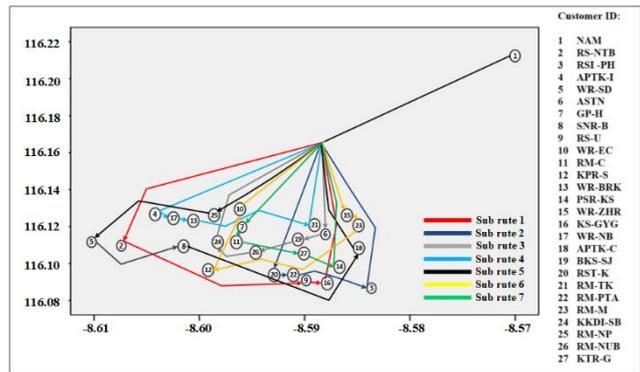

Figure 6. The Proposed Route

visiting four customers. In sub-route 6, the vehicle traveled to four customers and consumed 6.2126 liters of fuel. The vehicle fulfilled the demands of three customers in sub-route 7 and consumed 5.4243 liters of fuel.

Vehicle fuel consumption decreases due to the improvement of the traveled route produced by the model. Based on table 2 and table 3, travel distance and fuel consumption do not have a linear relationship. According to the US Department of Energy, (2008), fuel consumption increases by 2% for each additional load capacity of 100 pounds. Therefore, the highest customer demand in a routing plan is considered to be served first. The initial route yields a total distance and fuel consumption of 248.8 km and 50.5179 liters. Meanwhile, the proposed route produces fuel consumption of 44.0354 liters with a total distance of 252.9 km. The savings in fuel consumption are presented in Table 6.

The change of route sequence is affected by a load of each customer. The model aims to construct a route with the smallest amount of fuel consumption. It can be seen that sub-route 4 of the initial route (see table 4) has the shortest distance, which is 29.8 km, but the fuel consumption is quite high, as much as 7.1 liters. In table 1, the demand of customer-21 > customer-23, namely 665 kg and 591 kg. The early trip to customer-23 becomes a factor in the increase in fuel consumption. Hence, in sub-route 4 of the proposed route (see able 5), customer-21 is served first then followed by visits to other possible customers. Sub-route 2 (see Table 2) spends quite a high amount of fuel, 8.048 liters, with a distance of 32 km. Based on the demands in table 1, the demand for customer-8 < customer-11, which is 591 kg and 798 kg. The fact that the route-sequence puts customer-8 first causes a high fuel consumption because the vehicle travels to the next customer with a large weight of the load. Route improvement by the model will change the whole route in the system.

To measure the performance of the PSO algorithm on the fitness value, the number of population parameters (N) and the number of iterations are varied on each iteration of the experiment. Referring to research [52], the population size used in this study depends on the problem size. The population sizes used are 20, 30, 50, 100, 200, and 300. The number of iterations used during the experiment is 10, 30, 50, 100, 200, 300, 400, and 500. Table 6 presents a comparison of the total fuel consumption between the initial routes and the proposed routes. The total fuel consumption of the initial route is 50.5179 liters and the proposed route is 44.0354 liters. Therefore, the company saves 6.5 liters and equivalent to 13% which is less than the fuel consumption of the initial route.

Table 7. Vehicle Assignment of the Initial Route

Proposed route	Load Weight	Time Traveled (Hours)	Vehicle Assignment
1-2-1-26-27-1	2379	1.92	1
1-8-11-18-16-1	2393.5	2.25	
1-14-9-10-12-1	2383	1.88	
1-23-21-19-25-1	2356	2.2	
1-15-20-22-1	2203.5	1.92	2
1-3-4-7-26-1	2228.5	2.15	
1-24-5-17-1	2283	1.54	

Table 8. Vehicle Assignment of the Proposed Route

Proposed Route	Load Weight	Time Traveled (Hours)	Vehicle Assignment
1-2-9-16-1	1938	1.85	1
1-20-22-3-1	2389.5	1.58	
1-6-19-26-24-1	2484	1.92	
1-21-13-17-4-1	2242	1.75	
1-25-5-8-18-1	2365	2.12	2
1-15-23-12-10-1	2376	1.83	
1-11-7-27-14-1	2454	1.73	

In the initial condition, all sub-routes have been completed by two homogeneous vehicles. Besides, vehicles have limited travel time and capacity. Thus, the company introduces vehicle assignments for all sub-routes. During the research, we collected information about the assignment of vehicles to distribute the product. The vehicle assignment of the initial route is given in Table 7.

Table 7 shows that the first vehicle assignment holds 4 sub-routes. Each sub route consists of two factors, specifically load weight and travel time. There was no disruption of the weight of the vehicle. However, the total travel time on the first vehicle assignment exceeds 8 hours or T_max. The first vehicle spent 8.25 hours. On the other hand, the assignment of the second vehicle does not violate the weight of the load nor the travel time. The second vehicle spent 5.85 hours of travel time for serving customers.

In the current study, we proposed a model by considering the weight of the load and the travel time of the vehicle to produce a better route. According to Figure 2, this study has two constraints to determine the proposed route for satisfying customer demand. Vehicles have limited travel time and capacity so that it will produce several sub-routes. if Q>C and T>T_max then the vehicle can't visit the next customer and the next customer is assigned to a new sub route. all the sub-routes can't be completed by one vehicle. because the vehicle has a maximum time traveled (8 hours). Therefore, two vehicles will be assigned to visit customers. The vehicle assignments for the proposed route are presented in Table 8.

Sub-route 1 has a total travel time of 1.85 hours, sub-route 2 takes 1.58 hours of travel, vehicles passing sub-route 3 take 1.92 hours and sub-route 4 is 1.75 hours. The vehicle assignment was obtained from the total travel time that does not exceed its maximum limit. Consequently, the first vehicle is assigned to serve customers on four sub-routes. If the 5th sub-route is inserted
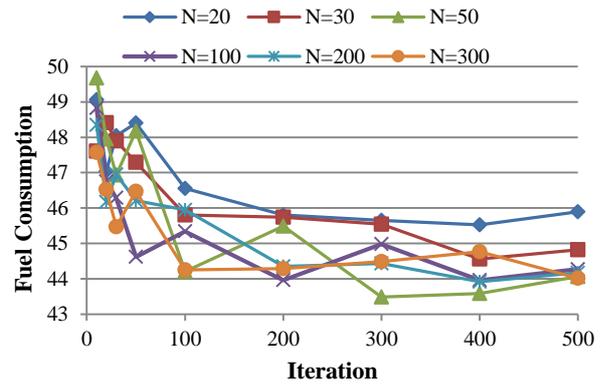

Figure 7. Iterations performance to the fitness value

in the first assignment, then the maximum travel time is disrupted. Therefore, the second vehicle is inserted into the next sub route.

The fitness value or total fuel consumption in a routing plan is highly dependent on the determined number of populations and iterations that are set. Based on figure 7, the population size was set to 20, 30, 50, 100, 200, and 300 and the iteration maximum varies between 30 and 500. The combination of population parameters and the number of iterations produces the best fitness value when N = 50 and the maximum number of iterations is 200. The fitness value represents the total fuel consumption of the vehicle in a routing plan. The smallest total fuel consumption obtained was 44.0354 liters and 7 sub-routes were formed as follows: 1 - 2 - 9 - 16 - 1; 1 - 20 - 22 - 3 - 1; 1 - 6 - 19 - 26 - 24 - 1; 1 - 21 - 13 - 17 - 4 - 1; 1 - 25 - 5 - 8 - 18 - 1; 1 - 15 - 23 - 12 – 10 - 1; 1 - 7 - 11 - 27 - 14 – 1. The route-sequence in the initial conditions is improved by the model, then produces a new proposed route with better vehicle fuel consumption. The fuel consumption of the initial route and the proposed route is 50.5179 liters and 44.0354 liters. Therefore, the company saves 6.5 liters, equivalent to 13% less than the fuel consumption of the initial route.

CONCLUSION

This paper has proposed a route division procedure by considering the total loading weight and total traveling time of a vehicle. Further, we have introduced the use of the PSO algorithm to obtain sub-routes to minimize fuel consumption. Implementing the proposed procedures and algorithms is carried out in real cases faced by bottled drinking water company. By comparing the fuel consumption on the company route and the proposed route, a savings of 13% is obtained on a particular day during observation. Further research needs to be conducted to prove the PSO algorithm's performance by determining the daily route for a month at the bottled drinking water company. In addition, the study can be developed by using benchmark instances and comparison of results with the algorithm proposed by previous researches.

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NOMENCLATURE

F_{ij}	total fuel consumption spent by vehicles from customer i to customer j
$F_{(s)(0)}$	fuel consumption from customer s to depot for empty vehicles
$F_{(0)(s)}$	fuel consumption from depot to customer s
d_{ij}	distance between customer i and customer j
MPG_{ij}	miles per gallon s the sequence of customers
Q	total loading weight of a vehicle
n	index of sub-route
TF	total vehicle fuel consumption of a routing plan
q_s	customer demand with sequence s
S	total number of customers
C	vehicle load capacity
$V_{i(t)}$	velocity of the ith particle in the swarm

L_n	current loading weight of nth sub-route
t_s	travel time of a vehicle to visit a customer
T	total travel time of a routing plan
T_{max}	maximum allowable travel time
$x_{i(t)}$	position of the ith particle in the swarm
c_1	cognitive acceleration coefficient
c_2	social acceleration coefficient
ω	inertia weight
r_1	random numbers within the interval [0, 1]
r_2	random numbers within the interval [0, 1]
N	number of populations
v	particle's velocity

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