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Procedia Computer Science 179 (2021) 920–929

Procedia Computer Science

www.elsevier.com/locate/procedia

5th International Conference on Computer Science and Computational Intelligence 2020

Distribution Cost Optimization Using Pigeon Inspired Optimization Method with Reverse Learning Mechanism

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Abstract

The goal of this research was to optimize the cost of goods distribution to some locations. The problem can be considered as Vehicle Routing Problem (VRP). The main characteristic of this problem is that the solution space expands exponentially. In our case at hand, the goods distribution that have been done, mostly done manually. Therefore, it may not optimize the costs of distribution. Manual optimization cannot be used if the number is locations is more than five because the solution space is too big to solve by hand. Pigeon Inspired Optimization (PIO) is proposed as a heuristic method for optimizing the VRP to optimize the cost and then it will be compared with Particle Swarm Optimization (PSO) method as comparison algorithm. Evaluation was conducted by comparing their performance in optimizing cost for several solution spaces. The achieved result is the shortest distribution path according to the constraints given and has lowest total cost of distribution. It can be concluded that PIO is better for optimizing the goods distribution path so that the distribution cost becomes minimal.

Peer-review under responsibility of the scientific committee of the 5th International Conference on Computer Science and Computational Intelligence 2020

Keywords: optimization; vehicle routing problem; pigeon inspired optimization; particle swarm optimization

1. Introduction

The distribution of goods or services is very important from the company's activities. A common problem with

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Peer-review under responsibility of the scientific committee of the 5th International Conference on Computer Science and Computational Intelligence 2020
10.1016/j.procs.2021.01.081

distribution is making decisions about optimizing routes that minimize travel time and the number of operating vehicles and other resources. Because of lack of control over distribution can cause losses for the company, then designing a good transportation system is expected to reduce the costs. One way to reduce transportation costs is to reduce transportation distance by optimizing routes. This problem can be considered as Vehicle Routing Problem (VRP). Before talking about VRP, we have to comprehend the traveling salesman problem (TSP) [1]. TSP considers a single vehicle visiting multiple customer locations before returning to the depot, and we want to minimize the total travel time or vehicle distance. VRP differs from TSP because VRP can generate multiple routes to pass through all customer locations [2]. The difference between TSP and VRP can be seen in Fig. 1, where VRP is a multiple-route node-service-combination problem and TSP is a single-route node-service-combination problem.

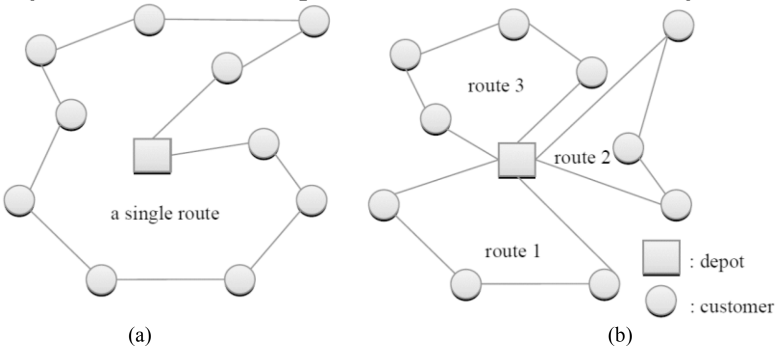

Fig 1. Different between: (a) traveling salesman problem (TSP) and (b) vehicle route problem (VRP)

Dantzig and Ramser first introduced the vehicle routing problem (VRP) in 1959 [3]. The VRP generalises the well-known travelling salesman problem (TSP). and bin packing problem (BPP). It is a combinatorial optimization and integer programming problem which found the optimal routes for distributing goods to some customer locations. To determine the optimal solution of VRP is NP-hard [4]. Therefore. the computational complexity of exact algorithms for solving VRP is exponential with the number of customer locations. As a result, the VRP tends to solve by using heuristics optimization to find workable solution with limited compute resource, such as particle swarm optimization (PSO) [5] and Artificial Bee Colony (ABC) [6]. The basic VRP involves a single depot, a set of customer locations and a fleet of vehicles at the depot. The objective of basic VRP is to minimize the total routing cost. Besides the basic VRP, there are many variations of VRP because there are many options in real case problem settings. In our research, we concern with the vehicle capacity limitation in real case problem. The fixed number of delivery vehicles with uniform capacity must service known customer demands from a common depot at minimum transit cost. This problem is called as Capacitated Vehicle Routing Problem (CVRP) [7]. In the CVRP, all customers must be visited once, each customer's request is known with certainty at the beginning and cannot be shared, the vehicles used are identical and have a capacity limit. Every customer has a request that must be fulfilled by every vehicle. Each customer's request can be different and the assignment of routes on each vehicle must pay attention to vehicle capacity. The total demand that must be fulfilled in each vehicle must not exceed the vehicle's capacity. The main challenge of CVRP is that the solution space or search space expands exponentially. This search space is the permutations of the order of routes. To grasp this problem, Fig. 2 shows the amount of search space in route optimization for one up to twelve customer locations or stores.

To optimize the distribution route, we can use the swarm intelligence algorithm. Swarm intelligence (SI) are optimization algorithms that are inspired by the phenomenon of biological intelligence from a herd of animals naturally. Swarm intelligence means that a herd that consists of many individuals without intelligence who show intelligent behaviour through simple cooperation between individuals [8]. In the case of CVRP, these individuals are represented by combinatorial locations to describe distribution routes in the search space. All the bio-inspired optimization algorithms are trying to simulate the emerged intelligent behaviour. They have significantly improved the feasibility of the modern optimization techniques by providing practical solutions. One swarm intelligence algorithm for solving CVRP is Particle Swarm Optimization (PSO) [3, 9, 10]. PSO works by having a population called as swarm for candidate solutions called as particles. These particles move over the search space and iteratively evaluate against certain objective function. Each particle guides its movement in the search space by combining information from its current value, its best value from previous locations (individual viewpoint) and best value locations with regards to all members of the swarm (communal viewpoint) [10]. The main weakness of PSO is when faces a very large search space. Because its exploratory behaviour is limited in certain area of search space. Therefore, PSO is not suitable for solving CVRP with many customer locations.

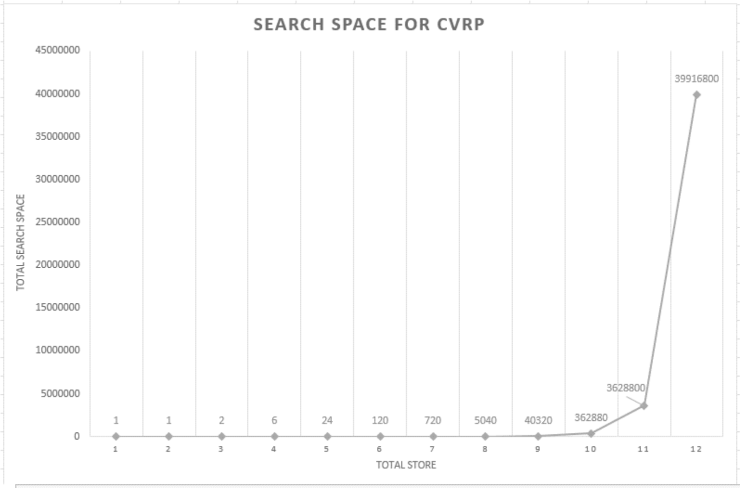

Fig 2. CVRP search space expands exponentially

Inspired by Zhong research [11], we proposed one relatively new SI algorithm, that is Pigeon Inspired Optimization (PIO). PIO is inspired by the behaviour of pigeons that have homing abilities [12]. In general, the search strategy of PIO algorithm is like PSO algorithm. However, the search strategy of PIO consists of two steps [13]. In the first stage, PIO searches in search space being guided by the best position found by the swarm and individual experience. In the second step, PIO is guided by the centre of the positions of remaining successful position. These two steps make PIO relatively can handle large search space. We implement both PSO and PIO algorithm and evaluate the performance in solving CVRP. Finally, experiments with real case dataset is done to measure how good this PIO comparing to PSO algorithm. The remainder of the paper is arranged as follows: first we discuss the methodology of our study in section 2, and then is followed by the experiment results in section 3. Finally, we concluded our work with suggestions for the next research in section 4.

2. Methodology

In this study, the main research question is how to handle the very large search space by means of swarm intelligent algorithm. Our main method is by experimenting with two algorithms: PSO and PIO and then analyze the results. The method of our study is using an experimental study, based on real case data on Capacitated Vehicle Routing Problem (CVRP). This problem can be expanded to be a very large search space case. We collect the data from real business to solve its problem of distribution of goods. The data are the number and type and volume of vehicles used for distribution, the names and addresses of company and customer warehouses, operational costs of distribution such as gas expenses, vehicle maintenance as well as driver and helper salaries, distance between depots and each store and the distance between each store, and other data that supports research. Based on these data, we formulated the Capacitated Vehicle Routing Problem (CVRP) and implemented the application software to calculate the PSO and PIO algorithms for solving it.

2.1 Capacitated Vehicle Routing Problem (CVRP)

Our research was conducted with identifying distribution problems first by interviewing stakeholders. Based on the dataset of the real case problem, we determine the problem boundaries as the scope of the study and set the problem objective, that is for minimizing the cost of distributing goods. Next, the model, called as Capacitated Vehicle Routing Problem (CVRP), is developed in the form of mathematical models based on literature [7], together with its problem boundaries. The mathematical model of CVRP is described as follows:

$$\text{Distribution cost total} = min\left(\sum(fixed\ cost + variable\ cost)\right)$$

Fixed cost = vehicle maintenance costs and driver and helper salaries
Variable cost = fuel cost
Notation:
i, j: *index of customer*; $i = 1 \ldots n, j = 1 \ldots n$; 0 *as a depot*
k: *index of the vehicle*; $k = 1 \ldots m$
c_ij: *distance from customer i and j*
p_k: *the price of fuel from vehicles k*
r_k: *ratio of fuel requirements of the vehicle k*
f_k: *maintenance costs and salaries of drivers and helpers from vehicles k*
Decision variable:

$$x_{ijk} = \begin{cases} 1, & \text{if vehicle k passes the route from i to j} \\ 0, & \text{elsewhere} \end{cases}$$

Objective function:

$$Z = min\left(\sum_{k=1}^{m}\sum_{j=0}^{n}\sum_{i=0}^{n}\frac{p_k}{r_k}c_{ij}x_{ijk} + \sum_{k=1}^{m} f_k\right)$$

The objective function of the model is to minimize the total distribution cost per one way which represents the total distribution cost. Additionally, the boundary functions are:

- Defines that each shop node is visited only once by one vehicle.

$$\sum_{i=0}^{n}\sum_{k=1}^{m} x_{ijk} = 1, \qquad \forall j = 1, 2, \ldots, n$$

$$\sum_{j=0}^{n}\sum_{k=1}^{m} x_{ijk} = 1, \qquad \forall i = 1, 2, \ldots, n$$

- Defines the number of vehicles entering and exiting the same depot.

$$\sum_{i=0}^{n} x_{i0k} - \sum_{j=0}^{n} x_{0jk} = 0, \qquad \forall k = 1, 2, \ldots, m$$

- If the vehicle visits the shop, the vehicle must also leave.

$$\sum_{i=0}^{n} x_{isk} - \sum_{j=0}^{n} x_{sjk} = 0, \qquad \forall s = 1, 2, \ldots, n;\ \forall k = 1, 2, \ldots, m$$

- Defines the number of vehicles that can be used.

$$\sum_{j=1}^{n} x_{0jk} \le 1, \qquad \forall k = 1, 2, \ldots, m$$

- Defines the relationship between two decision variables

$$\sum_{i=0}^{n} x_{ijk} = y_{jk}, \qquad \forall j = 0, 1, \ldots, n;\ \forall k = 1, 2, \ldots, m$$

$$\sum_{j=0}^{n} x_{ijk} = y_{ik}, \qquad \forall i = 0, 1, \ldots, n;\ \forall k = 1, 2, \ldots, m$$

- Defines that the load of goods does not exceed the capacity of the vehicle k

$$\sum_{j=1}^{n} d_j x_{0jk} \le Q_k, \qquad \forall k = 1, 2, \ldots, m$$

$$\sum_{i=1}^{n} d_i y_{ik} \le \sum_{k=1}^{m} Q_k, \qquad \forall k = 1, 2, \ldots, m$$

2.2 Pigeon Inspired Optimization (PIO)

Pigeon Inspired Optimization (PIO) Algorithm is proposed to solve the CVRP, especially when facing a very large search space. The PIO formulation uses two operators, namely: map and compass operator and landmark operator as follow:

1) Map and Compass Operator.

In this map and compass operator, rules are defined as follows:

x_i: the position of the dove i

v_i: pigeon speed i

where x_i and v_i are always updated every iteration. The new position of x_i and v_i speed of pigeon I in the t-iteration can be calculated by the following equation:

$$Vi(t) = Vi(t-1).e^{-Rt} + rand.\big(Xg - Xi(t-1)\big) \quad (1)$$

$$Xi(t) = Xi(t-1) + Vi(t) \quad (2)$$

where

R : map and compass factor

rand : random number [0,1]

x_g : current best global position

x_g can be obtained by comparing all positions between all pigeons.

2) Landmark Operators

Inside the landmark operator, a portion of the number of pigeons decreases in each generation. Pigeon is still far from their destination and they do not recognize the area. For example, Xc (t) as the canter of the position of several pigeons in the t-iteration and assume the pigeons can fly straight to their destination. The most recent position of pigeon i wheb the t-iteration is as follows:

$$Np(t) = \frac{Np(t-1)}{2} \quad (3)$$

$$Xc(t) = \frac{\sum Xi(t).fitness(Xi(t))}{Np\sum fitness(Xi(t))} \quad (4)$$

$$Xi(t) = Xi(t-1) + rand.(Xc(t) - Xi(t-1)) \quad (5)$$

Where fitness () is the quality equation of each dove. For minimum optimization,

$$fitness\big(Xi(t)\big) = \frac{1}{fmin\big(X(t)\big) + \varepsilon} \quad (6)$$

For each pigeon, the optimal position from iteration to Nc can be written as Xp, where

$$Xp = \min(Xi1, Xi2, \ldots, XiNc) \quad (7)$$

Reverse Learning Mechanism is applied to the PIO method to prevent local optima conditions in the PIO algorithm. In this mechanism, a reverse pigeon is formed which satisfies the following equation:

$$x_i' = a_i + b_i - x_i \quad (8)$$

where a_i and b_i are the upper and lower limits of the solution.

When making a selection, the fitness values of each individual in both populations are calculated, and if the individual fitness values are inversely higher than the original individual fitness values, the inverse individuals are maintained. If the opposite is true, then the original individual is retained. The next generation of the selected population remains unchanged. The added function of this mechanism is to accelerate the convergence of the algorithm, avoid local optima, and improve the performance of the algorithm to be able to reach the global optima faster.

2.2 Implementation

To implement PIO algorithm for solving the CVRP problem, we develop an application program. It is designed with the prototyping development method because the stakeholder can interact directly with the developer and is under a short development time. The application is created based on Python programming language and use SQL server to manage the dataset. The front end of this implementation can be seen in Fig 3. To evaluate the application whether it produces optimal results, we compare PIO algorithm with PSO algorithm to solve the similar problem. Furthermore, the application is evaluated based on its ease of use by interviewing all stakeholders.

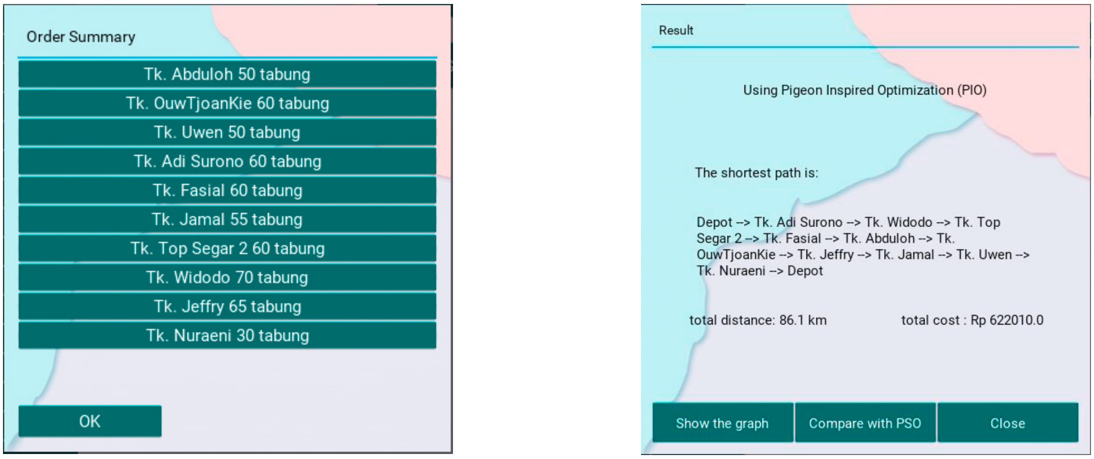

Fig 3. Front-end of PIO implementation software

3. Experiment Results

For experiments, we simulated 17 orders from different store locations. Store distance data is calculated using Google Maps. Table 1 shows the number of orders in each store and their shipping batch.

Table 1. The number of orders for each store

No	Store	Order amount (tube)	Shipping Batch
1	Tk. Dedi	90	I Total = 530
2	Tk. Eliana	80	
3	Tk. Endang	75	
4	Tk. Fatul	55	
5	Tk. H. Rikam	100	
6	Tk. Samlawi	60	
7	Tk. H. Selan	70	
8	Tk. OuwTjoanKie	55	II Total = 555
9	Tk. Abduloh	50	
10	Tk. Fasial	60	
11	Tk. Adi Surono	55	
12	Tk. Jamal	50	
13	Tk. Nuraeni	60	
14	Tk. Top Segar 2	65	
15	Tk. Widodo	55	
16	Tk. Uwen	50	
17	Tk. Jeffry	55	

The data to calculate the total distribution costs are as follows:

1. Fixed Cost:

The costs of a Mitsubishi Fuso vehicle per one way include:

- Maintenance costs: Rp. 15,000.00
- Driver and helper salaries: Rp. 500,000.00

2. Variable Cost:

Fuel prices
Mitsubishi Fuso: Rp. 8,700.00 / liter
ratio of fuel needs of each fleet
Mitsubishi Fuso: 7 km / liter

3. Volume

Fleet carrier tube volume:
Mitsubishi Fuso: 560 tubes

The used car can only deliver a maximum of 560 tubes. Based on this capacity, all orders in Table 1 can be divided into two batches, which contain 530 and 555 tubes respectively. We conduct two simulations for each batch as follow:

A. Simulation of route determination for shipping batch 1

After running the program 3 times, with 7 stores to visit, the number of pigeons used is 20, the number of iterations used is 10 iterations for map and compass operators and 5 iterations for landmark operators using the PIO algorithm, then obtained information in the following table.

Table 2. Results of the experimental application for distribution optimization by the PIO

Running	Optimal Route	Distance total (km)	Cost total (Rp)
1	Depot→Tk. Samlawi→Tk. Dedi→Tk. Eliana→Tk. Endang→Tk. Fatul→Tk. H. Selan→Tk. H. Rikam→Depot	104.1	644.381.43
2	Depot→Tk. H. Selan→Tk. H. Rikam→Tk. Fatul→Tk. Endang→ Tk. Eliana→Tk. Dedi→Tk. Samlawi→Depot	104.1	644.381.43
3	Depot→Tk. Samlawi→Tk. Dedi→Tk. Eliana→Tk. Endang→Tk. Fatul→ Tk. H. Rikam→ Tk. H. Selan→Depot	104.1	644.381.43

The total cost is obtained from the following calculation,

$$Z = \left(\frac{Rp\ 8.700/L}{7\ km/L} 104.1\ km + \text{Rp. } 500.000 + Rp.\ 15.000\right) = Rp.644.381.43$$

Where the total distance of the results of optimization is included in the calculation to determine the total distribution costs.

Based on Table 2, after running the program 3 times using the PIO method, there are 2 opposing solutions, namely running 2 and running 3. While running 1, the solutions found are different but have the same total distance. The opposite solution occurs because the solutions in the search space are permutations of the overall store sequence in which there is also a cyclic permutation in it. It can be concluded, by using the PIO method, 2 solutions are generated, namely Depot→Tk. Samlawi→Tk. Dedi→Tk. Eliana→Tk. Endang→Tk. Fatul→ Tk. H. Rikam→ Tk. H. Selan→Depot and Depot→Tk. Samlawi→Tk. Dedi→Tk. Eliana→Tk. Endang→Tk. Fatul→Tk. H. Selan→Tk. H. Rikam→Depot with a total distance of 104.1 km and a total cost of Rp. 644,381.43, of which the first solution is a cyclic permutation of Depot→Tk. H. Selan→Tk. H. Rikam→Tk. Fatul→Tk. Endang→Tk. Eliana→Tk. Dedi→Tk. Samlawi→Depot so it can be considered the same.

B. Simulation of route determination for shipping batch 2

After running the program 5 times, with 10 stores to visit, the number of pigeons used is 100, the number of iterations used is 20 iterations for map and compass operators and 10 iterations for landmark operators using the PIO algorithm, then information obtained in the following table

Table 3. Results of experimental application optimization of distribution by the PIO

Running	Optimal Route	Distance total (km)	Cost total (Rp)
1	Depot→Tk. Adi Surono→Tk. Widodo→ Tk. Fasial→ Tk . Top Segar 2→ Tk. OuwTjoanKie→ Tk. Jeffry→ Tk. Ab duloh→ Tk. Jamal→ Tk. Uwen→ Tk. Nuraeni→ Depot	86,7	622.755,71
2	Depot→Tk. Adi Surono→ Tk. Widodo→Tk. Top Segar 2 →Tk. Fasial→Tk. Abduloh→Tk. OuwTjoanKie→Tk. Jef fry→ Tk. Jamal→ Tk. Uwen→ Tk. Nuraeni→ Depot	86,1	622.010,00
3	Depot→Tk. Adi Surono→ Tk. Widodo→ Tk. Fasial→Tk . Top Segar 2→ Tk. Abduloh→Tk. OuwTjoanKie→Tk. J effry→ Tk. Jamal→ Tk. Uwen→Tk. Nuraeni→Depot	86,2	622.134,29
4	Depot→Tk. Nuraeni→Tk. Uwen→Tk. Jamal→Tk. Jeffry →Tk. OuwTjoanKie→ Tk. Abduloh→Tk. Fasial→Tk. T op Segar 2→Tk. Widodo→Tk. Adi Surono→ Depot	86,1	622.010,00
5	Depot→Tk. Adi Surono→ Tk. Widodo→Tk. Top Segar 2 →Tk. Fasial→Tk. Abduloh→Tk. OuwTjoanKie→Tk. Jef fry→ Tk. Jamal→ Tk. Uwen→ Tk. Nuraeni→ Depot	86,1	622.010,00

Based on table 3, after doing 5 running programs using the PIO method, obtained the same 3 optimal solutions, namely running 2, 4, and 5 with a total distance of 86.1 km, while the other 2 solutions are different and have a total distance of more big than that. The solutions produced on the 2nd and 5th runs are the same while the solutions on the 4th running are the reverse route of the 2nd and 5th running solutions. The resulting solutions are cyclic permutations. So that the three optimal solutions generated in running 2, 4 and 5 can both be recommendations for determining the company's distribution routes, i.e. Depot→Tk. Nuraeni→Tk. Uwen→Tk. Jamal→Tk. Jeffry→Tk. OuwTjoanKie→ Tk. Abduloh→Tk. Fasial→Tk. Top Segar 2→Tk. Widodo→Tk. Adi Surono→ Depot ataupun Depot→Tk. Adi Surono→ Tk. Widodo→Tk. Top Segar 2→Tk. Fasial→Tk. Abduloh→Tk. OuwTjoanKie→Tk. Jeffry→ Tk. Jamal→ Tk. Uwen→ Tk. Nuraeni→ Depot with a total distance of 86.1 km and a total cost of Rp 622,010.00.

C. Comparison to Particle Swarm Optimization (PSO)

The following is a comparison chart of the total distance of the solution produced using the PIO and PSO algorithms in the 1st and 2nd delivery batches which can be seen in Figure 4 and Figure 5.

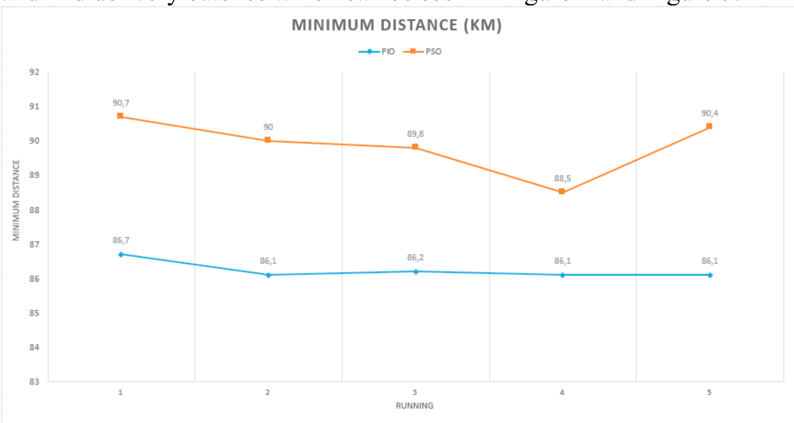

Fig 4. Comparison of the total distance between the PIO and PSO in batch II simulation

Based on Figure 4, after 3 attempts of calculation, it can be seen that each time the program runs, the PIO and PSO algorithms always produce the same total distance of 104.1 km for shipping goods to 7 stores. Whereas based on Figure 4, after 5 attempts of calculations were made, it was found that the PIO could produce a more optimal solution than PSO for the case of shipping to 10 stores. Here is a comparison chart of the solution between the PIO and PSO algorithms for shipping cases to 11 to 20 stores.

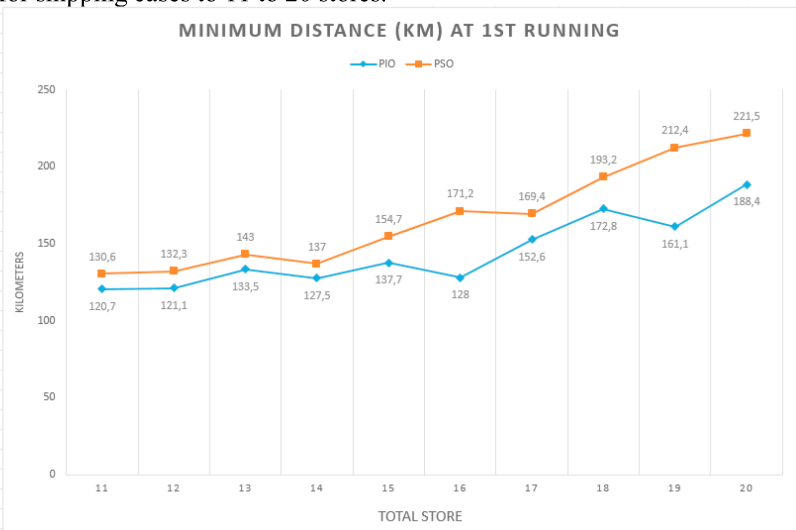

Fig 5. Comparison of the total distance between the PIO and PSO for 11 to 20 stores

The following is a comparison chart of the solution between the PIO and PSO algorithms for shipping cases to 25 to 60 stores.

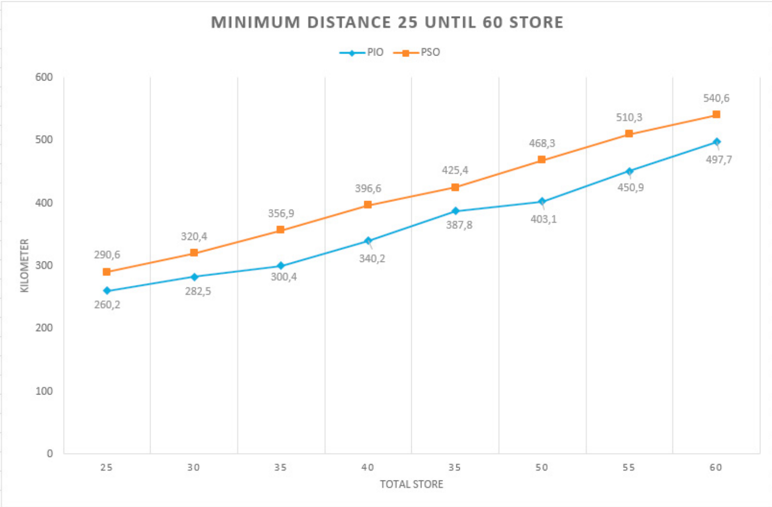

Fig 6. Comparison of the total distance between the PIO and PSO for 25 to 60 stores

Based on the graphs in Figure 4, Figure 5, and Figure 6, it can be concluded that the PIO algorithm produces the same solution for the case of delivery to 7 stores but is consistently able to produce more optimal solutions compared to the PSO method for route optimization with the number of stores is greater than 10.

In addition to the total distance comparison, another performance measurement of an optimization method is the convergence rate. Convergent is a condition where a population is centered towards 1 point. In this case, it can be seen in the graph in Figure 7, that the experience of fitness value that a population has shown whether it is convergent or not yet convergent for a generation of population. Figure 7 shows that when running to 1, the fitness value of the population using the PIO method is centered at one starting point on the 2nd iteration while the PSO method is only starting to focus on the 5th iteration. Therefore, it can be concluded that the PIO method converges faster than the method PSO.

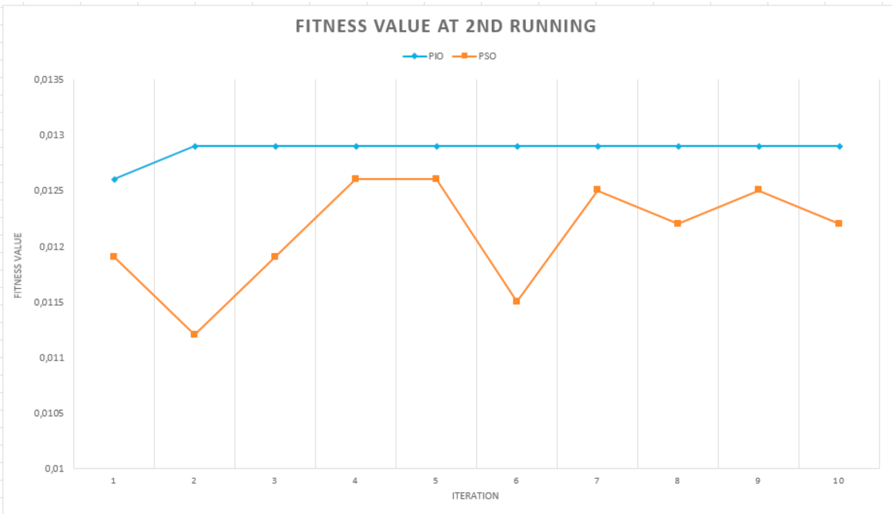

Fig 7. Comparison graph of the PIO and PSO fitness values on the 1st run

4. Conclusion

As conclusion based on our experiments, (1) PIO helps determine distribution routes more easily and optimally compared to manual calculations for large search spaces. (2) The route produced by the PIO algorithm is more optimal than that produced by the PSO for shipping to ≥10 stores. The PIO has a higher rate of convergence compared to the PSO algorithm. However, the processing speed of the PIO algorithm is lower compared to PSO. As suggestion, further application development is recommended to display the estimated travel time and route traveled in detail, as well as the use of maps and can display the shortest route for many vehicles.

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