Jurnal Teknik Industri
Vol. 23, No. 1, February 2022, pp. 31-42

ISSN : 1978-1431 print | 2527-4112 online

A Genetic Algorithm for Solving Periodic Heterogeneous Vehicle Routing Problem

Amelia Khoidir [a*], Annisa Kesy Garside [b]
[a] Department of Industrial Management, National Formosa University, Taiwan
[b] Department of Industrial Engineering, University of Muhammadiyah Malang, Indonesia
* Corresponding author: khoidir.amelia@gmail.com

ARTICLE INFO

Article history
Received October 25, 2021
Revised February 4, 2022
Accepted February 24, 2022
Available Online February 28, 2022

Keywords
Periodic Routing Problem
Heterogeneous Vehicles
Genetic Algorithm
Taguchi

ABSTRACT

This paper addresses the periodic heterogeneous vehicle routing problem (PHVRP), an extension of the classical vehicle routing problems (VRP). This problem is known to be confined to various real-world instances where each customer's demand should be served within a specific time horizon and a maximum demand quantity that can be delivered at each visit. The heterogeneous capacitated vehicles are available to perform the services for each customer. This paper aims to minimize the total traveling time of routes for all vehicles over the time horizon so that the customers' demands can be delivered. Thus, a novel coding scheme is also proposed to directly convert a random sequence of integers into a feasible solution, which is then embedded into algorithms. Furthermore, this paper also compares the performance of the Genetic Algorithm (GA) with the particle swarm optimization algorithm (PSO). The numerical results of the experiments show that the proposed GA is superior to PSO. However, the computation time of PSO is faster than GA.

1. Introduction

A basic vehicle routing problem (VRP) consists of a set of customers, each with a fixed quantity of demand, which must be served by a vehicle that travels from a depot to the customer and then returns to the depot [1-3]. Delivery routes of a vehicle must begin and end at the depot to ensure that all customer demands are satisfied and that each customer is visited by only one vehicle. Vehicle capacities are specified, and each vehicle frequently has a maximum total traveling length. Toth and Vigo [4] deal with the vehicle routing problem by creating a distribution scheduling plan in which vehicles are assigned to pick up and deliver products. The problem involves a single period, meaning that customer visit time starts at the beginning of the visit period and terminates when all customers have been served. Additionally, some real-life implementations are concerned with the periodic delivery operations during a specific time horizon, i.e., liquid petroleum of gasoline delivery, grocery delivery, or waste collections. According to Campbell and Wilson [5], periodic vehicle routing problems (PVRP) are an extension of the VRP in which

https://doi.org/10.22219/JTIUMM.Vol23.No1.31-42 http://ejournal.umm.ac.id/index.php/industri ti.jurnal@umm.ac.id

Please cite this article as: Khoidir, A., & Garside, A. K. (2022). A Genetic Algorithm for Solving Periodic Heterogeneous Vehicle Routing Problem. Jurnal Teknik Industri, 23(1), 31–42. https://doi.org/10.22219/JTIUMM.Vol23.No1.31-42

Jurnal Teknik Industri
Vol. 23, No. 1, February 2022, pp. 31-42

customers should be served at a particular frequency of visit according to a set schedule and receive a defined demand at each customer visit. The PVRP expands a single delivery period to T periods (T > 1), allowing each customer to require several services over the T period, i.e., within a one-week or one-month delivery period. Generally, VRP research focuses on reducing travel distances and times [6, 7]. Similarly, the PVRP needs to optimize each delivery period for a specific customer combination and the path selection for each delivery period to reduce the total traveling distance. Therefore, the PVRP is more complex than a classical VRP.

Beltrami and Bodin first applied PVRP to assign compactor trucks to a city waste collection [8]. Afterward, Chao, et al. [9] developed a heuristic method to solve the PVRP using the initialization and improvement phases. Baptista, et al. [10] presented an improved heuristic for solving the PVRP in waste paper box recycling. Francis, et al. [11] experimented with an improved heuristic algorithm for solving the PVRP using customer service frequencies as decision variables. Pourghaderi, et al. [12] developed a new simple, effective line construction heuristic algorithm for solving the PVRP using an embedded improvement procedure. Matos and Oliveira [13] experimented with the ant colony algorithm by suggesting a novel strategy to update the pheromone. Yu and Yang [14], proposed an ant colony algorithm based on two crossover operations to solve the PVRPTW. Garside and Laili [15] solved the periodic multi-trip vehicle routing problem using a cluster first route second heuristic. They found that the cluster first route second could generate a better routing solution. Some other heuristics for PVRP can be found in subsequent research [16-18].

This paper studies the periodic heterogeneous vehicle routing problem (PHVRP) motivated by the real-life scheduling of vehicles involving different vehicle capacities and periodic deliveries. In order to complete PHVRP, each delivery period must be optimized, as well as each delivery period using various vehicle capacities. Therefore, the PHVRP is embedded in the classical VRP. It is more complex since it includes an NP-Hard problem and can be solved using the exact and approximate method. According to researchers, there needs to be more literature relevant to the PHVRP. One related study is to develop an efficient technique for solving the periodic heterogeneous vehicle routing problem with driver scheduling using a heuristic algorithm and exact method [19]. Vidal, et al. [20] solved the multi-depot periodic vehicle routing problem in which the company has more than one depot and each depot has a different vehicle using a genetic algorithm. Furthermore, Cantu-Funes, et al. [21] solved the problem of the multi-depot periodic vehicle routing concerning the due dates and time windows. They solved the problem by using a mixed integer method and a reactive greedy randomized adaptive search procedure and determining the heterogeneous vehicles, the schedule of each vehicle, and the route between the factory and warehouse. Yao, et al. [22] solved the PVRP with different capacities of vehicles for each test problem. They developed an artificial bee colony algorithm by using a scanning strategy.

One of the approximate methods is the genetic algorithm (GA). GA is an evolutionary algorithm (EA) inspired by the natural selection mechanism introduced and initiated in 1970 by Holland. Researchers have drawn great attention to the GA due to its robustness and flexibility. Thus, the genetic algorithm has been used to solve various combinatorial problems, including certain types of vehicle routing difficulties [23]. This algorithm generally searches a very large and potentially high-dimensional search space. The genetic algorithm is a powerful component in a random search to solve uncertain and complex problems requiring a large time-space to find the optimal solution [24]. It is an effective process for finding a great solution set available for a specific design. Several researchers have successfully used the genetic algorithm in their studies [25-28]. The genetic algorithm was developed to solve the multi-depot vehicle routing problem Mirabi [29], where the hybrid genetic algorithm competes with previous methods regarding problem-solution quality. Nguyen, et al. [30] proposed the GA with two neighborhoods to solve the PVRP with time windows.

The goal of this paper is to minimize the total length traveled of routes for all vehicles during the time horizon so that customer demands are served. The rest of this paper is organized as follows. Section 2 describes the characteristic system, followed by a novel coding procedure, a description of the PVRP, the genetic algorithm, and the experimental setup using the Taguchi method. Section 3 presents the numerical and computational results of the genetic algorithm are discussed. The results are also compared with particle swarm optimization (PSO) in chapter 4. Conclusions of the paper and introduces possible future work are drawn in section 5.

2. Methods

2,1 Notation and Description of the PVRP

In general, periodic vehicle routing problems can be defined as a G = (C , E), where $C = (c_0, c_1, c_2, \dots . c_n)$ is the set that consists of subset $C = (c_1, c_2, \dots . c_n)$ which corresponds to the customers, and c_0 for the depot; and $E = \{d_{i,j} | c_{i,j} \in C,\ i \neq j\}$ is a set of distances, where $d_{i,j}$ represents the distance between c_i and c_j. A set of working days can be indexed by D = (1,2,..., T), where T denotes the total number of working days in a period length. The service demand of customer i can be denoted as r_i . Then let set $V = (v_1, v_2, \dots, v_k)$ as the vehicles at the depot, where k represents the total vehicles available at the depot. Additionally, the vehicle load capacity v is denoted as Q_v. As given by Chen, et al. [31], the mathematical model of the PVRP is as follows:

$$Objective = \min \sum_{i=0}^{n} \sum_{j=0}^{n} \sum_{t=1}^{T} \sum_{v=1}^{k} d_{i,j} z_{i,j,t,v} \tag{1}$$

Subject to:

$$\sum_{i=0}^{n} \sum_{j=0}^{n} z_{i,j,t,v} r_i \leq Q_v \qquad i \neq j, v \in V, t \in D \tag{2}$$

$$\sum_{v=1}^{k} z_{i,j,t,v} \leq 1, i, j (i \neq j) \in N, t \in D \tag{3}$$

$$\sum_{v=1}^{k} y_{t,v} \leq k, t \in D \tag{4}$$

$$z_{i,j,t,v} \in \{0,1\}, i\ , j\ (i \neq j) \in N, t \in D, v \in V \tag{5}$$

$$y_{t,v} \in \{0,1\}, t \in D, v \in V \tag{6}$$

In this thesis, the objective of the PVRP is to minimize the total traveling time to all customers over the planning period, as expressed in Equation (1). Equation (2), ensures the total delivery size by vehicle v must not exceed the vehicle capacities on day t. Equation (3), make sure that the frequency of visits of vehicle v from customer i to customer j is limited to once a day at maximum. As shown in equation (4), ensure that the total number of vehicles assigned on day t ($y_{t,v}$) is restricted to the total vehicles available at the depot. Additionally, equation (5), $z_{i,j,t,v} = 1$ indicates vehicle v performs the services from customer i to j on day t , while $z_{i,j,t,v} = 0$ indicating vice versa. Finally, in equation (6), $y_{t,v} = 1$ indicates that vehicle v is assigned to visit the customers on day t, while $y_{t,v} = 0$ indicating vice versa.

2.2 A Novel Coding Procedure

In this section, we provide a novel coding scheme to demonstrate the performance of each gene in the chromosome. The genetic algorithm has genetic operators, including crossover and mutation rates, which operate on the chromosome [32]. For a given chromosome that obtains by the encoding scheme, it is also required to know which permutation will correspond to [33]. This form of encoding allows genes that would help them to be constructed. Thus, the gene or chromosome is represented in this encoding scheme by a string of numbers representing its position in a sequence. The coding is based on the permutation of {1,2,…,n*max |b_i|}, where n describes the number of customers and max |b_i| describes the total maximal replenishment times for customers (maximum trips). The procedure of the novel coding is as follows:

The types of customer visit frequency for six days are shown in Table 1. The sequence used represents a visit frequency of six days from Monday to Saturday, with 1 indicating a visit and 0 otherwise.

Table 1. The Types of Customer Visit Frequency

Visit frequency	Visit day combination		
	1	2	3
2	100100	010010	001001
3	101010	010101	-
6	111111	-	-

Based on customers' visit frequency, generate a random integer sequence from {1,2,…,n*max |b_i|} to construct a feasible solution for PHVRP.

Compute {(Rand sequence + Normal sequence) mod T}+1 to find the type of visit frequency at each customer, where T is the number of possible types for customers' visit frequency.

Based upon step (3), compute the combination of vehicles for each day with {(Total of the random sequence at each day + mod K)}+1, where K is the total type of vehicle combinations. The results imply as follow:

- One big vehicle is adopted if the result = 1.
- One small vehicle is adopted if the result = 2.
- One big and one small vehicle are adopted if the result = 3.
- Two big vehicles are adopted if the result = 4.
- Two small vehicles are adopted if the result = 5.

2.3 A Genetic Algorithm

Based on the novel coding scheme, we embedded the novel coding into a genetic algorithm. The GA can be described as a stochastic search algorithm inspired by natural competition between individuals to appropriate limited sources [34, 35]. The genetic algorithm effectively solves high computational complexity problems, including VRP. According to Rao, et al. [36], the computational procedure of the proposed GA to solve the PHVRP is classified as follows.

Define an appropriate chromosome to represent design parameters. Define the population in which consists of several groups of chromosomes, and the chromosomes are

ISSN : 1978-1431 print | 2527-4112 online

organized into gene strings. To initiate, the maternal chromosomes are generated at random as the initial population.

Evaluate the fitness value or objective function. The fitness value in the genetic algorithm defines how close the obtained solution is to the optimal solution for the desired problem.

Apply the crossover rate and the mutation rate. The genetic algorithm needs to carry out the crossover and mutation rate operations to maintain the group's diversity and reduce errors. In this paper, we used Taguchi to find the best crossover and mutation rates, as shown in Table 2.

```
Algorithm
Initialization
Select parameters (crossover rate, mutation rate, affinity)
Generate an initial population based on the string number of the novel encoding
scheme
Repeat
while Total_iter<=Total_iter_max do
    Evaluate the fitness of each individual in the population
        for each individual
            Calculate the fitness function
        end
        for i=1:length (Fitness ), then sort generation by using
            x = min (Fitness) -Fitness (i);
        end
        Then set as Gbes
    Calculate the weight of each individual
    FIT = (Fitness − min(Fitness)) / ((max(Fitness)−min(Fitness)) + 0.0000001;
    Maintenance of the fittest cell before maturation retains good value
    Create a mating pool using a Roulette wheel
    Perform the crossover operation
    Perform the mutation of individuals
    Evaluate the new individuals
    Update the population of the next generation
End while
Until the stopping condition is satisfied
Print the current best solution
```

Fig. 1. Procedure of genetic algorithm

The selection procedure was used to select genes from previously formed chromosomes. The Roulette Wheel Selection (RWS) method was one of the most commonly used selection methods. The parents obtained the chromosome's fitness value proportion using this method. The chromosome with the highest fitness value has been selected to have a higher probability than the other. Chromosome parents selected in the following selection process started the crossover process to produce offspring chromosomes. During the crossover process, the genotypes of both parents are merged to produce a new child.

Moreover, due to the high probability that the child will be exposed to further mutations with certain gene modifications. This aids in furthering the exploration of the solution area and ensuring or preserving genetic diversity. Meanwhile, the population must have the right balance of quality and genetic diversity to support efficient search.

Please cite this article as: Khoidir, A., & Garside, A. K. (2022). A Genetic Algorithm for Solving Periodic Heterogeneous Vehicle Routing Problem. Jurnal Teknik Industri, 23(1), 31–42. https://doi.org/10.22219/JTIUMM.Vol23.No1.31-42

Repeat step 3 until the maximum number of generations is achieved. The procedure of the genetic algorithm is presented in Fig. 1.

2.4 Distribution Problem

Table 2. Visit Frequency and Demand Quantity of the Customers

Once per day		Once per 2 days		Once per 3 days	
Node	Demand	Node	Demand	Node	Demand
5	15	4	7	1	20
13	10	8	10	2	22
18	25	9	10	3	15
22	27	16	15	6	12
24	20	19	25	7	15
		21	10	10	17
		23	15	11	20
				12	15
				14	18
				15	12
				17	20
				20	10

The distribution problem considers the real-life instances of a distributor of liquefied petroleum gas (LPG) based in Batu, Indonesia. The distributor has 24 customers to be replenished frequently based on their given needs. Large and small vehicles with different capacities are available at the depot to serve every customer in each period. The working days of vehicles delivering the products are 6 days, from Monday to Saturday. The details of visit frequency and demand quantity of each customer are shown in Table 2. Some assumptions in this paper are as follows:

Each vehicle starts and terminates at the same depot. Each vehicle only visits each customer once after the scheduled delivery. Since the vehicle has a quantity, it can make multiple trips if the total quantity demand of all customers on day t exceeds its capacity.

There are five combinations of vehicles to be assigned each day: one big vehicle (M), one small vehicle (m), two big vehicles ($M_1 + M_2$), two small vehicles ($m_1 + m_2$), and one big vehicle and one small vehicle (M + m). The vehicles' capacity is set as 180 for the big vehicle and 60 for the small vehicle.

2.5 Experimental Setup

The genetic algorithm's initialization process needs to set some basic parameters. The correct choice of parameters will greatly affect the effectiveness of an algorithm. Setting different parameters of the Genetic Algorithm will produce different optimal results. Even if the same parameters are used in the algorithm, the results will still be different due to the randomness stochastic solution. The stochastic solution-search design is typical of the GA. The Taguchi method's main goal is to find optimal parameters to reduce this randomness. This paper provides the Taguchi Method to obtain the best parameter. Taguchi has been successfully applied in various experiments [37, 38]. The Taguchi model is based on optimizing key metrics known as signal-to-noise ratios (SNR) by conducting experiments using orthogonal arrays [39]. The mean square deviation of the objective function is called the signal-to-noise ratio (η). To calculate the stochastic

Please cite this article as: Khoidir, A., & Garside, A. K. (2022). A Genetic Algorithm for Solving Periodic Heterogeneous Vehicle Routing Problem. Jurnal Teknik Industri, 23(1), 31–42. https://doi.org/10.22219/JTIUMM.Vol23.No1.31-42

disturbance characteristics, each group of orthogonal table parameters was run 10 times for each experiment to represent the equivalence characteristics. Taguchi defined as,

$$\eta = -10\log\left(\frac{1}{n}\sum_{t=1}^{n} y_t^2\right) \tag{7}$$

Equation (7) is Taguchi's as defined for *the smaller* the better characteristic. Where $\{y_1, y_2, \dots, y_n\}$ denotes the objective function of experiments evaluation value. Thus, this paper adopted a three-level orthogonal array, a standard L_9 (3^2) array. The parameter combinations adopted in this paper are as follows: crossover rate (P_c) and mutation rate (P_m) as demonstrated by Hoogeboom, et al. [40], Mansour [41], and Ahmadi, et al. [42]. The overall computational result for the experiments is defined in Table 3. Thus, the result shows that the best parameter of crossover rate is 0.99 and 0.03 for mutation rate, with the lowest η = -59.864 indicating the optimal level.

The experimental results were performed using MATLAB R2015b software on Acer with specification Intel ® Core ™ i7 – 3770 CPU @ 3.40G Hz 64–bit and RAM 3.68 GB.

Table 3. Numerical Result of Parameters of GA

Factor		Objective										SNR (η)
P_c	P_m	y_1	y_2	y_3	y_4	y_5	y_6	y_7	y_8	y_9	y_{10}	
0.7	0.02	941.7	1030.7	946.5	936.8	935.6	1017.9	1063.7	1033.7	943.2	1006.2	-59.884
0.7	0.006	1039.1	1051.2	1031.1	942.8	1030.4	1037.6	987.0	943.6	934.4	1056.0	-60.055
0.7	0.03	1031.0	1035.4	1025.8	1017.6	931.5	1043.0	1041.4	1029.7	936.2	1109.0	-60.183
0.02	0.02	951.1	1030.1	1029.3	1030.2	1038.9	1028.3	1039.0	934.7	1021.2	1130.9	-60.211
0.02	0.006	1006.8	1019.5	1029.7	1033.2	1020.5	1032.2	1045.0	1048.3	1037.2	1039.1	-60.267
0.02	0.03	1105.7	1036.8	1079.5	1110.2	1045.0	1119.8	933.6	1122.8	937.5	1023.7	-60.453
0.99	0.02	1092.9	1044.1	1029.5	1032.9	1106.5	1035.4	936.5	1038.6	944.7	934.3	-60.182
0.99	0.006	938.3	1114.2	939.2	1050.8	938.7	1027.3	1052.5	1052.9	938.6	939.6	-60.011
0.99	0.03	1020.0	1018.9	1039.9	937.5	1034.3	937.0	933.0	1041.6	944.7	926.4	-59.864

Population = 100, generation = 2000, affinity = 0.9.

3. Results and Discussion

This paper aims to minimize all customers' travel time over the planning period. Furthermore, the data related to the demand of each customer, the distant matrix, and the service schedule of each customer are collected in this research. Table 3 and Table 4 shows the computational and numerical results.

The solution of GA and PSO can be seen in Table 4. The combination of vehicles assigned to serve customers on day one is one big vehicle (M) with a total demand of 169 and a total traveling time of 141.5044 minutes for the GA. Similarly, the combination of vehicles assigned to serve the customer for day one of PSO is one big vehicle (M) with a total demand of 174 and a total traveling time of 147.4264 minutes. On day two, one big vehicle is assigned with a demand of 152 and a total traveling time of 144.3194 minutes for GA, while the total demand and traveling time of PSO are 150 and 163.0126, respectively. However, a combination of big and small vehicles (M+m) are assigned to serve customers on day three, with a loaded vehicle, 171 for big vehicles and 57 for small vehicles for GA. As well as PSO, the load of big vehicles is 173 and small vehicles is 57. The combination of vehicles to serve on day 4 is a big vehicle and a small vehicle (M+m) with the load vehicles for the big and small vehicles 124 and 47 for GA, and one big vehicle

Please cite this article as: Khoidir, A., & Garside, A. K. (2022). A Genetic Algorithm for Solving Periodic Heterogeneous Vehicle Routing Problem. Jurnal Teknik Industri, 23(1), 31–42. https://doi.org/10.22219/JTIUMM.Vol23.No1.31-42

Jurnal Teknik Industri
Vol. 23, No. 1, February 2022, pp. 31-42

with a loaded vehicle 169 for PSO. Next, on day five, one big vehicle (M) is assigned to serve the customer with a load is 155 for GA and 152 for PSO. Henceforward, the combination of big vehicle and small vehicle (M+m) are assigned to serve customers on day three with the load vehicles 171 for big vehicle and 59 for the small vehicle for GA. As well as PSO, the load of big vehicles is 173 and small vehicles is 57. Thus, the total traveling time is 1027.5960 minutes for GA and 1072.2484 minutes for PSO.

Table 4. The solution of the GA and PSO

Visit Day	Vehicle	GA		PSO	
		Total Demand	Travelling Time (minutes)	Total Demand	Travelling Time (minutes)
1	Big	169	141.5044	174	147.4264
	–	0	–	–	–
2	Big	152	144.3194	150	163.0126
	–	0	–	–	–
3	Big	171	164.4546	173	154.5005
	Small	57	63.0376	57	63.0376
4	Big	124	142.2784	169	167.0226
	Small	47	15.4052	–	–
5	Big	155	149.1824	152	147.8264
	–	–	–	–	–
6	Big	171	149.4104	173	169.6786
	Small	59	58.0035	57	59.7436
Total			1027.5960		1072.2484

Table 5. The Comparison of the Numerical Result of 30 Experiments

Description	GA			PSO		
	Objective	CPU Time	Iteration	Objective	CPU Time	Iteration
Min	997.23	578.28	364	1020.92	123.91	150
Average	1001.52	590.65	1810	1079.25	125.09	764
Max	1046.66	607.44	3685	1094.16	126.45	1582
Standard Deviation	34.82	8.76	244.7	37.43	0.76	313.7

Based on the result, it can be seen that the combination of the vehicle is only one big vehicle, and one big vehicle and one small vehicle. It implies that the company only requires one big vehicle and one small vehicle that should be available to deliver the product each day.

As shown in Table 5, the minimal objective of 100 experiments of GA is 997.23, and PSO is 1020.92, which means the min objective value of GA is superior to PSO. The computation time of the GA is longer than those of PSO, where the maximum CPU time of GA is 607.44, and PSO is 126.45. The PSO computation time is faster than GA because PSO can be implemented without many operators and parameters, such as crossover and mutation rates. GA can be implemented with many operators and parameters. GA also has higher computation efforts than PSO because PSO updates particles by themselves with the internal velocity and has a memory, which is important to the algorithm. The GA converges with minimal iterations is 364 and 150 for the PSO. The result implies that GA is outperformed, but PSO is superior in terms of iteration, computation time, and simplicity in finding the solution.

4. Comparison of Genetic Algorithm and Particle Swarm Optimization

To analyze the genetic algorithm, we also compared the objective result of the genetic algorithm and particle swarm optimization based on the average objective of numerical results with 30 experiments. We used the independent sample t-test to test further the genetic algorithm's performance and particle swarm optimization. We further test the following hypothesis with $\alpha = 0{,}025$.

The average objective of numerical results with 30 experiments can be seen in Table 6. As Shown in Table 7, the result of the t-test is -7.251 with a probability of 0.000, where less than α (0.025). Thus, it implies that the GA is significantly superior to PSO. Additionally, the average value of the GA is lower than that of the PSO. It can be concluded that the total traveling time of the GA is shorter than the total traveling time of the PSO, so it implies that GA outperforms the PSO.

Table 6. The average objective of numerical results with 30 experiments

GA	999.26	1031.37	1037.38	1019.28	1038.44	1021.22	1010.38	1024.67	1039.20	1044.97
	1010.77	1036.62	999.01	1040.21	1040.47	1019.44	1037.94	1022.35	1011.15	1001.96
	1004.45	1044.28	1022.87	1041.31	1007.88	1025.68	1007.38	1005.05	1019.51	1036.32
PSO	1024.49	1074.16	1059.80	1051.28	1044.01	1084.68	1057.59	1073.73	1059.28	1033.46
	1042.24	1050.52	1079.64	1032.02	1081.28	1058.32	1035.16	1034.48	1051.94	1074.88
	1093.99	1078.25	1021.91	1048.17	1058.98	1035.62	1047.63	1092.13	1046.46	1086.05

Table 7. The result of the statistical test of GA and PSO

Methods	Mean	t	P Value
GA	1023.36	-7.251	0.000
PSO	1057.07		

5. Conclusion

This paper has proposed a genetic algorithm to solve the periodic heterogeneous vehicle routing problem (PHVRP). The objective is to minimize the total traveling time during the distribution. Using an orthogonal array, we used the Taguchi method to find the best crossover rate and mutation rate of the genetic algorithm. The real case of PHVRP in Batu City, Indonesia has been solved using the genetic algorithm. Furthermore, the numerical results show that PSO's objective value is greater than GA's. However, the computation time is faster than those of GA. Additionally, the statistical test show that the average objective of GA is superior to those of PSO. In future research, a possible algorithm improvement could also involve comparing results with the proposed algorithm.

Declarations

Author contribution: All authors contribution in this paper.
Funding statement: No funding was received for this work.
Conflict of interest: The authors declare no conflict of interest.
Additional information: No additional information is available for this paper.

References

[1] D. M. Utama, B. N. I. Farida, U. Fitriani, M. F. Ibrahim, and D. S. Widodo, "Hybrid Henry Gas Solubility Optimization: An Effective Algorithm for Fuel Consumption Vehicle Routing Problem," *Jurnal Ilmiah Teknik Industri,* vol. 20, no. 2, pp. 141-152, 2021. https://doi.org/10.23917/jiti.v20i2.15640.

[2] D. M. Utama, T. A. Fitria, and A. K. Garside, "Artificial Bee Colony Algorithm for Solving Green Vehicle Routing Problems with Time Windows," *Journal of Physics: Conference Series,* vol. 1933, no. 1, p. 012043, 2021. https://doi.org/10.1088/1742-6596/1933/1/012043.

[3] D. M. Utama, D. S. Widodo, M. F. Ibrahim, and S. K. Dewi, "A New Hybrid Butterfly Optimization Algorithm for Green Vehicle Routing Problem," *Journal of Advanced Transportation,* vol. 2020, p. 8834502, 2020. https://doi.org/10.1155/2020/8834502.

[4] P. Toth and D. Vigo, *Vehicle routing: problems, methods, and applications*. SIAM, 2014.

[5] A. M. Campbell and J. H. Wilson, "Forty years of periodic vehicle routing," *Networks,* vol. 63, no. 1, pp. 2-15, 2014. https://doi.org/10.1002/net.21527.

[6] D. M. Utama, S. K. Dewi, A. Wahid, and I. Santoso, "The vehicle routing problem for perishable goods: A systematic review," *Cogent Engineering,* vol. 7, no. 1, p. 1816148, 2020. https://doi.org/10.1080/23311916.2020.1816148.

[7] S. K. Dewi and D. M. Utama, "A New Hybrid Whale Optimization Algorithm for Green Vehicle Routing Problem," *Systems Science & Control Engineering,* vol. 9, no. 1, pp. 61-72, 2021. https://doi.org/10.1080/21642583.2020.1863276.

[8] E. J. Beltrami and L. D. Bodin, "Networks and vehicle routing for municipal waste collection," vol. 4, no. 1, pp. 65-94, 1974. https://doi.org/10.1002/net.3230040106.

[9] I. M. Chao, B. L. Golden, and E. Wasil, "An improved heuristic for the period vehicle routing problem," *Networks,* vol. 26, no. 1, pp. 25-44, 1995. https://doi.org/10.1002/net.3230260104.

[10] S. Baptista, R. C. Oliveira, and E. Zúquete, "A period vehicle routing case study," *European Journal of Operational Research,* vol. 139, no. 2, pp. 220-229, 2002. https://doi.org/10.1016/S0377-2217(01)00363-0.

[11] P. Francis, K. Smilowitz, and M. Tzur, "The Period Vehicle Routing Problem with Service Choice," *Transportation Science,* vol. 40, no. 4, pp. 439-454, 2006. https://doi.org/10.1287/trsc.1050.0140.

[12] A. R. Pourghaderi, R. Tavakkoli-Moghaddam, M. Alinaghian, and B. Beheshti-Pour, "A simple and effective heuristic for periodic vehicle routing problem," in *2008 IEEE International Conference on Industrial Engineering and Engineering Management*, 2008, pp. 133-137. https://doi.org/10.1109/IEEM.2008.4737846.

[13] A. C. Matos and R. C. Oliveira, "An Experimental Study of the Ant Colony System for the Period Vehicle Routing Problem," in *Ant Colony Optimization and Swarm Intelligence*, Berlin, Heidelberg, 2004, pp. 286-293: Springer Berlin Heidelberg. https://doi.org/10.1007/978-3-540-28646-2_26.

[14] B. Yu and Z. Z. Yang, "An ant colony optimization model: The period vehicle routing problem with time windows," *Transportation Research Part E: Logistics and Transportation Review,* vol. 47, no. 2, pp. 166-181, 2011. https://doi.org/10.1016/j.tre.2010.09.010.

[15] A. K. Garside and N. R. Laili, "A Cluster-First Route-Second Heuristic Approach to Solve The Multi-Trip Periodic Vehicle Routing Problem," *Jurnal Teknik*

Industri, vol. 20, no. 2, pp. 172-181, 2019. https://doi.org/10.22219/JTIUMM.Vol20.No2.172-181.
[16] G. Paletta, "The period traveling salesman problem: a new heuristic algorithm," *Computers & Operations Research,* vol. 29, no. 10, pp. 1343-1352, 2002. https://doi.org/10.1016/S0305-0548(01)00035-1.
[17] L. Bertazzi, G. Paletta, and M. G. Speranza, "An improved heuristic for the period traveling salesman problem," *Computers & Operations Research,* vol. 31, no. 8, pp. 1215-1222, 2004. https://doi.org/10.1016/S0305-0548(03)00075-3.
[18] R. A. Russell and D. Gribbin, "A multiphase approach to the period routing problem," *Networks,* vol. 21, no. 7, pp. 747-765, 1991. https://doi.org/10.1002/net.3230210704.
[19] E. M. Panggabean, H. Mawengkang, Z. Azis, and R. Filia Sari, "Periodic Heterogeneous Vehicle Routing Problem With Driver Scheduling," *IOP Conference Series: Materials Science and Engineering,* vol. 300, no. 1, p. 012017, 2018. https://doi.org/10.1088/1757-899X/300/1/012017.
[20] T. Vidal, T. G. Crainic, M. Gendreau, N. Lahrichi, and W. Rei, "A Hybrid Genetic Algorithm for Multidepot and Periodic Vehicle Routing Problems," *Operations Research,* vol. 60, no. 3, pp. 611-624, 2012. https://doi.org/10.1287/opre.1120.1048.
[21] R. Cantu-Funes, M. A. Salazar-Aguilar, and V. Boyer, "Multi-depot periodic vehicle routing problem with due dates and time windows," *Journal of the Operational Research Society,* vol. 69, no. 2, pp. 296-306, 2018. https://doi.org/10.1057/s41274-017-0206-7.
[22] B. Yao, P. Hu, M. Zhang, and S. Wang, "Artificial bee colony algorithm with scanning strategy for the periodic vehicle routing problem," *Simulation,* vol. 89, no. 6, pp. 762-770, 2013. https://doi.org/10.1177/0037549713481503.
[23] B. M. Baker and M. A. Ayechew, "A genetic algorithm for the vehicle routing problem," *Computers & Operations Research,* vol. 30, no. 5, pp. 787-800, 2003. https://doi.org/10.1016/S0305-0548(02)00051-5.
[24] M. A. Mohammed, M. K. Abd Ghani, R. I. Hamed, S. A. Mostafa, M. S. Ahmad, and D. A. Ibrahim, "Solving vehicle routing problem by using improved genetic algorithm for optimal solution," *Journal of Computational Science,* vol. 21, pp. 255-262, 2017. https://doi.org/10.1016/j.jocs.2017.04.003.
[25] G. Zhenfeng, L. Yang, J. Xiaodan, and G. Sheng, "The Electric Vehicle Routing Problem with Time Windows using Genetic Algorithm," in *2017 IEEE 2nd Advanced Information Technology, Electronic and Automation Control Conference (IAEAC)*, 2017, pp. 635-639. 10.1109/IAEAC.2017.8054093.
[26] P. Li, J. He, D. Zheng, Y. Huang, and C. Fan, "Vehicle Routing Problem with Soft Time Windows Based on Improved Genetic Algorithm for Fruits and Vegetables Distribution," *Discrete Dynamics in Nature and Society,* vol. 2015, p. 483830, 2015. https://doi.org/10.1155/2015/483830.
[27] Y. P. Anggodo, A. K. Ariyani, M. K. Ardi, and W. F. Mahmudy, "Optimization Of Multi-Trip Vehicle Routing Problem With Time Windows Using Genetic Algorithm," *Journal of Environmental Engineering and Sustainable Technology; Vol 3, No 2 (2016)DO - 10.21776/ub.jeest.2017.003.02.4,* vol. 3, no. 2, pp. 92-97, 2017. http://dx.doi.org/10.21776/ub.jeest.2017.003.02.4.
[28] C. Yaw and C. Lin, "Solve the vehicle routing problem with time windows via a genetic algorithm," *Conference Publications,* vol. 2007IS - SpecialSP - 240, p. 249, 2007. https://doi.org/10.3934/proc.2007.2007.240.

[29] M. Mirabi, "A novel hybrid genetic algorithm for the multidepot periodic vehicle routing problem," *AI EDAM,* vol. 29, no. 1, pp. 45-54, 2015. https://doi.org/10.1017/S0890060414000328.

[30] P. K. Nguyen, T. G. Crainic, and M. Toulouse, "A hybrid generational genetic algorithm for the periodic vehicle routing problem with time windows," *Journal of Heuristics,* vol. 20, no. 4, pp. 383-416, 2014. https://doi.org/10.1007/s10732-014-9244-3.

[31] R.-M. Chen, Y.-M. Shen, and W.-Z. Hong, "Neural-like encoding particle swarm optimization for periodic vehicle routing problems," *Expert Systems with Applications,* vol. 138, p. 112833, 2019. https://doi.org/10.1016/j.eswa.2019.112833.

[32] M. F. Ibrahim, F. R. Nurhakiki, D. M. Utama, and A. A. Rizaki, "Optimised Genetic Algorithm Crossover and Mutation Stage for Vehicle Routing Problem Pick-Up and Delivery with Time Windows," *IOP Conference Series: Materials Science and Engineering,* vol. 1071, no. 1, p. 012025, 2021. https://doi.org/10.1088/1757-899X/1071/1/012025.

[33] N. Choubey, "A Novel Encoding Scheme for Traveling Tournament Problem using Genetic Algorithm," *International Journal of Computer Applications,* vol. 2, no. 7, pp. 79-82, 2010. http://dx.doi.org/10.5120/1536-139.

[34] S. Gholizadeh, "Structural Optimization for Frequency Constraints," *Metaheuristic Applications in Structures and Infrastructures,* pp. 389-417, 2013. http://dx.doi.org/10.1016/B978-0-12-398364-0.00016-4.

[35] M. F. Ibrahim, M. M. Putri, D. Farista, and D. M. Utama, "An Improved Genetic Algorithm for Vehicle Routing Problem Pick-up and Delivery with Time Windows," *Jurnal Teknik Industri,* vol. 22, no. 1, pp. 1-17, 2021. https://doi.org/10.22219/JTIUMM.Vol22.No1.1-17.

[36] S. S. Rao, T.-S. Pan, and V. B. Venkayya, "Optimal placement of actuators in actively controlled structures using genetic algorithms," *AIAA Journal,* vol. 29, no. 6, pp. 942-943, 1991. https://doi.org/10.2514/3.10683.

[37] G. Taguchi, "Introduction to quality engineering (White Plains, NY: Asian Productivity Organization, Unipub/Kraus International Publications)," 1986.

[38] M. S. Phadke, *Quality engineering using robust design*. Prentice Hall PTR, 1995.

[39] J.-T. Tsai, W.-H. Ho, T.-K. Liu, and J.-H. Chou, "Improved immune algorithm for global numerical optimization and job-shop scheduling problems," *Applied Mathematics and Computation,* vol. 194, no. 2, pp. 406-424, 2007. https://doi.org/10.1016/j.amc.2007.04.038.

[40] M. Hoogeboom, W. Dullaert, D. Lai, and D. Vigo, "Efficient Neighborhood Evaluations for the Vehicle Routing Problem with Multiple Time Windows," *Transportation Science,* vol. 54, no. 2, pp. 400-416, 2020. https://doi.org/10.1287/trsc.2019.0912.

[41] R. F. Mansour, "Using Genetic Algorithm for Identification of Diabetic Retinal Exudates in Digital Color Images %J Journal of Intelligent Learning Systems and Applications," vol. 4, no. 4, pp. 188-198, 2012. http://dx.doi.org/10.4236/jilsa.2012.43019.

[42] A. Ahmadi, F. E. Bouanani, H. Ben-Azza, and Y. Benghabrit, "A Novel Decoder Based on Parallel Genetic Algorithms for Linear Block Codes %J International Journal of Communications, Network and System Sciences," vol. 6, no. 1, pp. 66-76, 2013. http://dx.doi.org/10.4236/ijcns.2013.61008.

Please cite this article as: Khoidir, A., & Garside, A. K. (2022). A Genetic Algorithm for Solving Periodic Heterogeneous Vehicle Routing Problem. Jurnal Teknik Industri, 23(1), 31–42. https://doi.org/10.22219/JTIUMM.Vol23.No1.31-42