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Genetic Algorithm with Cluster-first Route-second to Solve the Capacitated Vehicle Routing Problem with Time Windows: A Case Study

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Abstract: In a distribution problem, designing the right distribution route can minimize the total transportation costs. Therefore, this research aims to design a distribution route that produces a minimal distribution distance by clustering the demand points first. We generated the clustering method to cluster the demand points by considering the proximity among the demand points and the total vehicle capacity. In solving this problem, we are using p-median to determine the cluster and a genetic algorithm to determine the distribution route with the characteristics of the CVRPTW problem. CVRPTW or capacitated vehicle routing problem with time windows is a type of VRP problem where there is a limitation of the vehicle capacity and service time range of its demand point. This research concludes that clustering the demand points provides a better result in terms of total distribution costs by up to 16.26% compared to the existing delivery schedule. The performance of the genetic algorithm shows an average difference of 1.73%, compared to the exact or optimal method. The genetic algorithm is 89.68% faster than the exact method in the computational time.

Keywords: Cluster-first route-second, P-median clustering, genetic algorithm, CVRPTW.

Introduction

Distribution and marketing activities play an essential role in ensuring the successful sale of a product. In distribution activities, choosing the right distribution route can minimize the total cost of transporttation. Transportation costs are known to have a proportion of 29.4% of the total logistics costs [1]. This paper considers a real-world problem where a manufacturer distributes products to retailers with different demands, heterogeneous fleets, capacitated vehicles, limitation of demand point's service time. Another interest is the large number of demand points.

Coca-Cola Amatil Indonesia or CCAI is a Fast-Moving Consumer Goods company that focused on selling soft drinks. In implementing its distribution system, CCAI considers the limitations on their demand point's service time windows, as well as the capacity of their vehicle. The distribution routes problem at CCAI is a Capacitated Vehicle Routing Problem or CVRP with time windows or CVRPTW. In this study, clustering of its demand points will be carried out first by considering the cluster capacity and proximity among the demand points. Besides, there are 225 demand points and 15 vehicles available. The CCAI Medan implemented a distribution system intuitively. It is not based on theoretical calculations to optimize the distribution system. Figure 1. shows the mapping of the current distribution system delivery day. Based on these problems we want to give the alternative solution to make the distribution system more efficient than the existing condition.

To solve this problem, we proposed a cluster first route second approach. The idea of this solution involves two stages of decisions (1) partitioning the outlet locations by considering its capacity and distance first, which differs this paper from several previous papers, and (2) sequencing the delivery in each cluster to get the assignment and routes of the vehicle. Several problems implemented this approach, such as for solving ambulance routing problem [2], two-echelon location routing optimization [3], application in waste collection problem [4]. First, implement the p-median method for clustering, considering the proximity among the demand points and the total fleet capacity available each day. The cluster indicates the working days for the distribution. Because there are five working days of delivery, so the number of clusters is five. K-Clustering, especially k-median and k-means, is the most popular model to solve the general clustering problem [5]. In this problem, we used the Capacitated P-Median Problem (CPMP) using Integer Linear Programming

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(ILP). In the works of literature, there is extensive research using the P-Median problem. Mai *et al.* [6] using the capacitated p-median problem to test the proposed algorithm in which the observations consist of geographic locations of customers and the corresponding demand of these customers. Garcia *et al.* [7] used p-median problem with radius formulation to solve a large problem using heuristics approach. The algorithm proposed performs very well in general based on reduced formulation. Elloumi and Tighter [8] proposed a new formulation by a mixed-integer linear problem using a branch and cut algorithm. Puerto *et al.* [9] solved a discrete location problem using p-median and analyzed from the sum, maximum, and coverage point of view.

Many modern routing applications use the CVRPTW model, such as grocery home-delivery systems [10]. Several methods are proposed in the literature to solve this problem, such as mixed-integer programming, heuristics [11], and stochastic programming [12]. Then the routing is carried out using the genetic algorithm method, considering the time windows of each demand point and the vehicle capacity. This research uses a Genetic Algorithm ([13,14]). Applying the genetic algorithm in some VRP cases effectively and efficiently in terms of the computation results in reasonable computational time, and the proposed solutions produce a feasible fitness value. [15] who also use GA for routing problems state that using this algorithm produces consistent results.

The insertion method is one of the well-known methods to solve the VRP problem. It is introduced by [16], who examined VRPTW problems with the cluster-first route-second method with the urgency clustering method. Besides, the exact mix integer programming method is also often used in VRP problems; one of these is used by [17]. They examined CVRPTW problems as well as the cluster-first route-second technique with the k-means clustering method. Genetic algorithm methods applied in this research are also commonly used in VRP problems, such as research conducted by [18]. They examined CVRPTW problems using the cluster-first route-second method with the k-means clustering method.

Methods

The first step to solve this problem is to develop a cluster for customers based on the distance matrix using P-Median. P-median is generally a method for solving location-allocation problems, aiming to minimize the total distance from each demand point to the closest number of supply points [19]. Moreover, P-median can also be applied for clustering problems. As a clustering method, P-median can partition data sets into groups or clusters. Those clusters are built based on the proximity of the data [20]. This research uses the P-Median clustering method since it considers the distance as well as the capacity. P-Median clustering guarantees that the number of demands in a cluster will not exceed the cluster's capacity.

CVRPTW or capacitated vehicle routing problem with time windows is one type of VRP problem, where there are limitations in vehicle capacity and service time windows of each demand point. Molina *et al.* [21] also conducted research related to the CVRPTW problem under resource limitation and more than one type of vehicle. This research could be categorized as a HFVRPTW-LR problem or heterogeneous fleet vehicle routing problem with time windows and limited resource. Furthermore, Ferreira *et al.* [22] also researched VRPTW problems. However, the contrast between the previous study and this study is that there is more than one service period or time window at each demand point. Apart from the two studies above, Tohidifard *et al.* [23] also researched VRPTW problems. The mathematical of CVRPTW [24] is formulated as follows:

Objective function:

$$\min \sum_{i=1}^{N} \sum_{j=1}^{N} \sum_{k=1}^{N} D_{ij} C\, X_{ijk} \quad (1)$$

Constraints:

$$\sum_{i=1}^{N} \sum_{k=1}^{N} X_{ijk} = 1, \text{for } j = 1, \dots, N-1 \quad (2)$$

$$\sum_{j=1}^{N} \sum_{k=1}^{N} X_{ijk} = 1, \text{for } i = 1, \dots, N-1 \quad (3)$$

$$\sum_{i=1}^{N} \sum_{j=1}^{N} Q_i X_{ijk} \le P_k, \text{for } k = 1, \dots, y \quad (4)$$

$$\sum_{i=1}^{N} X_{ijk} - \sum_{i=1}^{N} X_{jik} = 0, \text{for } k = 1, .., y; j = 1, \dots, N \quad (5)$$

$$\sum_{j=1}^{N} X_{ojk} = 1, for\ k = 1, \dots, y \quad (6)$$

$$\sum_{i=1}^{N} X_{i,n+1,k} = 1, for\ k = 1, \dots, y \quad (7)$$

$$X_{ijk}\left(W_{ik} + S_i + t_{ij} - W_{jk}\right) \le 0 \quad (8)$$

$$E \le W_{ik} \le b_i \quad (9)$$

$$W_{ik} + S_i + t_{ij} - W_{jk} \le M_{ij}\left(1 - X_{ijk}\right) \text{for } k = 1, \dots, y;\ \forall\ (i, j) \in A \quad (10)$$

$$f_i \le W_{ik} \le b_i \quad (11)$$

$$X_{ijk} = 0 \text{ or } 1 \quad (12)$$

Where:

Q_i	:	demand for outlet i
D_{ij}	:	distance from outlet i to j
S_i	:	service time of outlet i
C	:	fuel price per meter consumption
X_{ijk}	:	binary, 1 if vehicle k is used to serve outlet i to j; 0 otherwise
P_k	:	maximum capacity of vehicle k
W_{ik}	:	starting service time of outlet i by vehicle k
W_{jk}	:	finishing service time of vehicle k in outlet j
E	:	earliest departure time
L	:	latest departure time
i, j	:	index of outlet to be served
k	:	index of vehicle
0	:	index of depot

N	:	number of outlets (depot included)
y	:	number of vehicles
A	:	set of arcs (i, j)
f_i, b_i	:	time windows of outlet i

The objective function is to minimize the total distribution costs by multiplying the total distance traveled and fuel cost. Constraints (2) and (3) indicate that an outlet is only served by one vehicle. Constraint (4) indicates that the number of products does not exceed the vehicle's total capacity. Constraint (5) indicates that the vehicle will immediately leave outlet i towards the outlet j after finishing serving outlet i. Constraint (6) shows that the vehicle leaves the depot to carry out distribution. Constraint (7) shows that the vehicle will return to the depot after serving all outlets. Constraint (8) shows the total service time of the vehicle k. Constraint (9) indicates that vehicle k cannot serve outlet i before its upper limit and does not perform service beyond its lower limit. Constraint (10) indicates that vehicle k cannot serve outlet j before it finishes serving outlet i. Constraint (11) shows that vehicle k is can only serve outlets at a certain time.

A genetic algorithm or GA is a method based on natural selection mechanisms and natural genetics [25]. Genetic algorithm refers to the theory of evolution by Charles Darwin, where individuals who can survive are the good ones. A fitness value represents the measure of good in the GA. The pseudocode for finding a solution using the genetic algorithm method is as follows:

1. Set Parameters
2. Generate initial solution using permutation representation
3. Calculate fitness
4. While nth iteration process < Set of Iteration **do:**
    If random number ≤ Crossover Rate do
    Crossover using partially mapped crossover (PMX)
    if random number ≤ Mutation Rate do
    Mutation
Selection
5. **End while**
6. Select the best fitness
7. Return to the best solution

The proposed GA produces distribution routes. The route sequences are represented using gene permutations. In this study, we generated 300 population, i.e., 300 candidate sequences of genes or distribution routes. Here are two examples of initial solutions in cluster 1 before the crossover and mutation process is carried out:

Solution 1:

14	0	0	0	12	0	0	7	0	13	10	0	5	0	2	8	6	0	0	0	0	0	11	4	15	9	0	3	1

Solution 2:

0	0	13	2	0	10	0	0	0	0	15	0	8	0	0	12	0	7	11	0	0	0	3	4	5	6	9	14	1

In terms of crossover operation, the method used is PMX or partially mapped crossover. PMX Crossover is carried out using the following steps:

1. Initialize parent 1 and parent 2 which are represented as P1 and P2 according to solutions 1 and 2. Columns with a yellow highlight show the crossover indication points.

P1	14	0	0	0	12	0	0	7	0	13	10	0	5	0	2
	8	6	0	0	0	0	0	11	4	15	9	0	3	1	
P2	0	0	13	2	0	10	0	0	0	0	15	0	8	0	0
	12	0	7	11	0	0	0	3	4	5	6	9	14	1	

2. Next, the 0 value in the core solution is substituted into a negative number which aims to avoid bias in the search process in the program, so that the solution becomes:

P1	14	-1	-2	-3	12	-4	-5	7	-6	13	10	-7	5	-8	2
	8	6	-9	-10	-11	-12	-13	11	4	15	9	-14	3	1	
P2	-1	-2	13	2	-3	10	-4	-5	-6	-7	15	-8	8	-9	-10
	12	-11	7	11	-12	-13	-14	3	4	5	6	9	14	1	

3. While the value in other points is changed to X. O1 and O2 represent the offspring 1 and 2 obtained from this crossover process.

O1	X	X	X	X	X	X	X	X	X	-7	X	X	X	-9	X
	X	X	X	X	X	X	X	X	X	X	X	X	X	X	
O2	X	X	X	X	X	X	X	X	X	13	X	X	X	-8	X
	X	X	X	X	X	X	X	X	X	X	X	X	X	X	

4. Furthermore, each X value is replaced according to the values in its respective parent, if there is a similarity in value between points on one offspring, then the value at that point is still written as x

O1	14	-1	-2	-3	12	-4	-5	7	-6	-7	10	X	5	-9	2
	8	6	X	-10	-11	-12	-13	11	4	15	9	-14	3	1	
O2	-1	-2	X	2	-3	10	-4	-5	-6	13	15	X	8	-8	-10
	12	-11	7	11	-12	-13	-14	3	4	5	6	9	14	1	

For example, the values that should be at the 12th and 18th points on offspring 1 are -7 and -9, while the -7 and -9 values are the results of the crossover at the 10th and 14th points, thus the values at the 12th and 18th points are still written as X.

5. Then the X value is filled in according to the value of the opposite parent, for example, the 12th and 18th values on offspring 1 are filled according to the value in parent 2 which is not owned by offspring 1, which is read from left to right.

O1	14	-1	-2	-3	12	-4	-5	7	-6	-7	10	13	5	-9	2
	8	6	-8	-10	-11	-12	-13	11	4	15	9	-14	3	1	
O2	-1	-2	-7	2	-3	10	-4	-5	-6	13	15	-9	8	-8	-10
	12	-11	7	11	-12	-13	-14	3	4	5	6	9	14	1	

6. The final step is to change the negative value back to 0

O1	14	0	0	0	12	0	0	7	0	0	10	13	5	0	2
	8	6	0	0	0	0	0	11	4	15	9	0	3	1	
O2	0	0	0	2	0	10	0	0	0	13	15	0	8	0	0
	12	0	7	11	0	0	0	3	4	5	6	9	14	1	

After the crossover is carried out, the offspring that has been obtained through the crossover process is mutated.

1. Initialize parent 1 and parent 2. Columns highlighted in yellow indicate the mutation points

P1	14	0	0	0	12	0	0	7	0	0	10	13	5	0	2
	8	6	0	0	0	0	0	11	4	15	9	0	3	1	
P2	0	0	0	2	0	10	0	0	0	13	15	0	8	0	0
	12	0	7	11	0	0	0	3	4	5	6	9	14	1	

2. The value of 0 at these points is also substituted with a negative number which also aims to avoid bias in the scattering process

P1	14	-1	-2	-3	12	-4	-5	7	-6	-7	10	13	5	-9	2
	8	6	-8	-10	-11	-12	-13	11	4	15	9	-14	3	1	
P2	-1	-2	-7	2	-3	10	-4	-5	-6	13	15	-9	8	-8	-10
	12	-11	7	11	-12	-13	-14	3	4	5	6	9	14	1	

3. Furthermore, the mutation points are carried out by changing the value at the samae offspring's two mutation points, example, the value at the 10th point on offspring 1 is changed to the value at the 14th point on offspring 1, and vice versa.

O1	14	-1	-2	-3	12	-4	-5	7	-6	-9	10	13	5	-7	2
	8	6	-8	-10	-11	-12	-13	11	4	15	9	-14	3	1	
O2	-1	-2	-7	2	-3	10	-4	-5	-6	-8	15	-9	8	13	-10
	12	-11	7	11	-12	-13	-14	3	4	5	6	9	14	1	

4. The final step is to change the negative number back to 0

O1	14	0	0	0	12	0	0	7	0	0	10	13	5	0	2
	8	6	0	0	0	0	0	11	4	15	9	0	3	1	
O2	0	0	0	2	0	10	0	0	0	0	15	0	8	13	0
	12	0	7	11	0	0	0	3	4	5	6	9	14	1	

While the selection process in GA in this study uses the roulette wheel method which step is as follow:
1. Calculate the fitness of the initial population
2. Calculate the probability of each accepted chromosome
3. Calculate the cumulative probability (q) in each chromosome. If the n[th] chromosome is $q_{n-1} <$ $random\ number < q_n$, then the chromosome is selected for the next process.

Results and Discussions

Clustering is carried out using the p-median approach and generated using LINGO 18.0. The data inputs are the number of working days, the cluster capacity, the total of all available fleet capacity in a day, the demand of all outlets, and the distance among the outlet obtained using the QGis software. This process resulted in 5 clusters representing the days of distribution and summarized in Figure 2.

Before running the genetic algorithm we need to set the tuning parameters, they are the number of iteration, number of population, crossover rate and mutation rate. We set the number of iteration as 100 and 300, number of population 50 and 100, crossover rate 0.5 and 0.9, mutation rate 0.1 and 0.5. Those setting parameters was experimented in the third cluster since it represents the average number of demands. One Factor at a Time (OFAT) is used to tune the parameters. In each experiment, we replicate a set of tuning paramters 30 times. The results is summarized in Table1.

Table 1 and Figure 3 show that the more iterations and populationn, the objective function will reach miniminum value. It is also time consuming. In the setting parameters, the fitness function reach minimum at 300 iterations, 100 population, with cross over and mutation rate 0.5. It needs 59.5 seconds to find the minimum fittess function at Rp 1,301,854.

Based on the previous best parameter setting, we run the GA to find the minimized objective function. Additionally, to the setting paramter, we generated a random number between 0 and 1 ($0 \leq r \leq 1$) to represent the crossover and mutation process in the GA algorithm. If the r is smaller or equal to the mutation and/or crossover rate, then the mutation and crossover can be executed. The minimum fitness function is reached at the 672[nd] iteration (see Figure 4).

VRP problems are np-hard problems, which means that these problems cannot be solved optimally in the polynomial timeframe. Therefore, the heuristic and metaheuristic methods are considered quite efficient in solving this problem. However, to compare whether

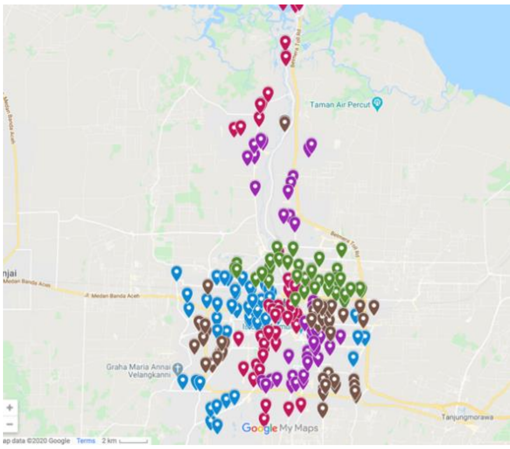

Figure 1. Mapping of real condition

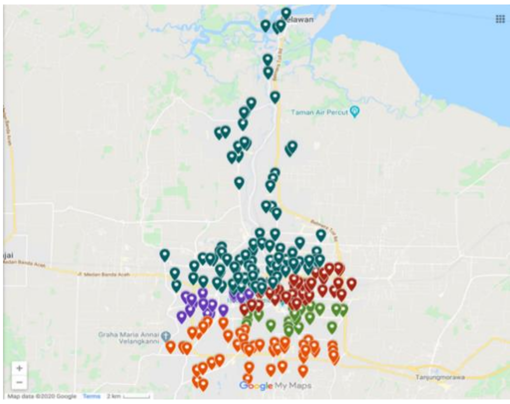

Figure 2. Mapping after clustering

heuristic and metaheuristic algorithms' output is good enough, it is necessary to compare the exact method's output with smaller data instances. Therefore, in this study, the exact method is also applied to solve routing problems in 3 instances, namely instance 1 with five nodes of demand points, instance 2, or cluster 1 with 15 nodes of demand points. The objective function values and the route generated through calculations using the exact method will then be compared with the genetic algorithm's objective function value.

Furthermore, to test the genetic algorithm's performance, the GA routing results of 5 nodes and 15 nodes routing are compared with the result obtained using exact methods. The comparison is based on the objective function and computation time results.

Table 2 shows that solving the 5-points CVRPTW problem using the exact method requires a shorter computation time (CT) than genetic algorithms. However, solving CVRPTW in the 15-point case using the exact method requires a significantly longer computation time than the computation time required to use genetic algorithms. Where the average difference in the objective function (OF) between the exact method and the genetic algorithm

Table 1. Tunning parameter

Niter	Npop	Xover Rate	Mut Rate	Objective function (Rp)	Comp time (s)
100	50	0.9	0.1	1,350,391	72
100	50	0.5	0.5	1,331,958	69.52
300	100	0.9	0.1	1,331,958	39.52
300	100	0.5	0.5	1,301,854	59.5

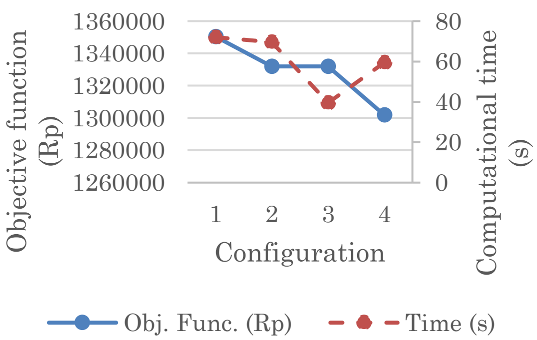

Figure 3. Tunning parameter graph

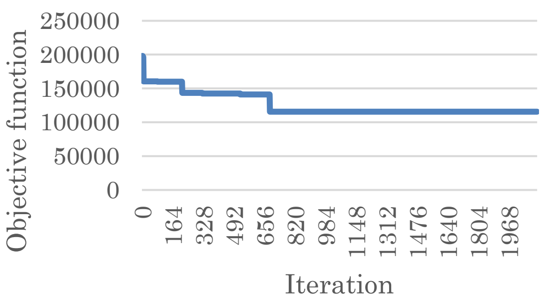

Figure 4. Proposed GA convergency

Table 2. Exact and GA comparison

Node	Obj Function (OF) Exact (Rp)	GA (Rp)	Comp Time (CT) Exact (s)	GA (s)	Gap OF (%)	CT (%)
5	89,063	89,063	0.38	0.06	0	84.21
15	291,870	301,974	660	32	3.46	95.15
Average gap			1.73%		89.68%	

means in both cases is 14.375%. It shows that using genetic algorithms on a larger scale will be more efficient than using the exact method and will not show any different results than the optimal results.

Next, we compared the results of the proposed solution to the real condition, which only used an intuitive solution. Table 3 summarizes those comparisons. It exhibits that the proposed solution reduced transportation costs by 16.26%. In this proposed solution, Cluster 3 and Cluster 5 have higher transportation costs than the real condition. It happened since; those clusters are dense. There are many depots to visit. While Cluster 1, Cluster 2, and Cluster 4 have less transportation cost than the existing condition. Figure 1 and Figure 2 show cluster differences. Table 4 shows the statistics summary for each cluster.

Table 3. Trasportation ost between the existing and prossed GA

Day / Cluster	Existing Condition	Proposed GA
Mon / C1	1,510,106	308,190
Tue / C2	1,622,894	480,130
Wed / C3	595,270	1,329,308
Thu / C4	983,762	840,605
Fri / C5	1,384,786	2,147,124
Total	6,096,818	5,105,369
Gap (Rp)	991,458	
Gap (%)	16.26%	

Table 4. Statistical summary of the proposed GA

Cluster	Objective function (Rp) Mean	Stdev	Computational time (s) Mean	Stdev
C1	309,467	2,785	30.3	3.28
C2	480,130	8,285	37.93	2.85
C3	1.329,308	48,187	83.3	3.09
C4	840,605	3,090	72.27	1.34
C5	2,147,124	19,672	93.57	1.57
Total Cost/Week	5,106,636		322.37	

Conclusion

The proposed solution using clustering and GA algoritm reduced the distribution cost by 16.26%. It is well-known that solving routing problem using meta-heuristics approach will not reach global optimum. However, the computation time is reasonable compared to solve using the linear model (exact method). The objective function of the two methods shows an average difference of 1.73%. The difference in computation time in instances with the 15 points between the genetic algorithm and the exact method is 89.68%. It shows that the use of the genetic algorithm is considered effective enough to solve large-scale problems. Overall, the genetic algorithm method used in this research is a basic GA method, and the clustering is generated by only considering the distance of each outlet and the daily capacity. However, using another clustering method to cluster the demand points might be worth considering as well in considering the balance of the data in each cluster. Finding efficient solution procedures remains an open avenue for future research.

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