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Ant Colony Optimization Using Different Heuristic Strategies for Capacitated Vehicle Routing Problem

Siti Fatimah Mohamad Ayop [1], Mohd Shahizan Othman[2], Lizawati Mi Yusuf[3]

[1,2,3] School of Computing, Faculty Engineering, Universiti Teknologi Malaysia

E-mail: sfatimah226@live.utm.my

Abstract. Capacitated Vehicle Routing Problem (CVRP) is a variant of vehicle routing problem (VRP) in which vehicles with restricted capacities required to pick-up or deliver at various locations. The main constraint in CVRP is to pick-up or deliver the goods for the least cost without exceeding the vehicle capacity. Therefore, the main objective of this paper is to minimize the distance travelled by vehicles. Hence, this paper proposed to use Ant Colony Optimization (ACO) with different heuristic strategies to optimize the distance travelled by the vehicles while not exceeding the vehicle capacities. Swapping, reversion, and insertion are the heuristic strategies used to examine the efficiency of neighbour creations in ACO. Christofides data sets are utilized in this paper to experiment on the solution construction in ACO with different heuristic strategies. The results showed that the use of ACO is efficient using the swap, reverse and insert strategies for distance minimization but there are possibilities for the vehicle visiting the same customer more than once. Meanwhile ACO with random combination with swap, reverse and insert are capable to solve CVRP without any possibilities for the vehicle visiting the same customer more than once.

1. Introduction

Vehicle Routing Problem (VRP) is an enhancement from Travelling Salesman Problem (TSP) that aimed to find the optimum travel distance with a single vehicle and a single route. Exact methods are used to solve TSP, but this method unable to solve real-world cases since the data are getting larger in recent years and TSP only include a single vehicle. To solve these problems, VRP was introduced [1]. VRP can solve the problem efficiently and more applicable to real-world cases since it is involved in a single depot with multi-vehicles. Capacitated Vehicle Routing Problem (CVRP) is one of the Vehicle Routing Problem (VRP) variants. CVRP is an extended variant that concerns to serve the customers without violating the vehicles. There are many real-life applications such as logistics, transportation and distribution used CVRP to solve the problems [2].

2. CVRP Formulation

There are terms and notations to fulfil all the constraints in CVRP. The terms are defined as follow [2]:

a) $G = (V, E)$, $V = \{V_0, V_1 \ldots, V_n\}$, refers on undirected graph that includes a set of vertex $\{V_0, V_1 \ldots, V_n\}$ referred to customers' demand, and E is the possibilities to all connection.

b) Vehicles can serve many customers from start to end in the same depot, but the total demand capacity should not exceed the vehicle capacity, Q.

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c) Traveling distance between customers will be calculated using Euclidean distance formula, $d=\sqrt{\left(X_n-X_{n+1}\right)^2+\left(Y_n-Y_{n+1}\right)^2}$ where *X* and *Y* are referred as customer coordinates while *n* referred as customer position.

Following are the objective constraints to solve CVRP:
a) Routing involves a single depot.
b) Vehicle must start and end at the same depot.
c) Every route should have a demand; zero demands are not allowed.
d) Capacity demand must not exceed vehicle capacity.
e) Vehicle use is homogeneous.
f) Each customer can be visited by only one vehicle for one time.

3. Ant Colony Optimization

ACO is a swarm intelligence population-based algorithm introduced by [3]. This algorithm has been inspired by real ant behaviour designed originally for the traveling salesman problem (TSP). ACO is a metaheuristic method used frequently by researchers to solve CVRP. This method is introduced with ant nature whereby ant as the vehicle, food as the customer, nest as the depot, trail as the route and the pheromone concentration that will provide the best way for distance optimization. This algorithm used pheromone as an indirect medium for communication on trails for step-by-step solution route constructions. More concentration of pheromone attracts ants for better route distance optimization. As a result, more attraction for the ants will increase the convergence speed in ACO.

The objectives of this research were to optimized distance travelled by the vehicle. Achieving all constraints in CVRP is important to reduce the distance travelled efficiently. There are researchers who suggested to use cluster-first route-second [4, 5] for distance optimization. Implementing cluster method is a good step [6, 7], but to increase the optimization distance performance, solution construction in ACO is very important to achieve the objective without visiting customers more than one and exceeding vehicle capacities [8, 9].

3.1. Solution Construction

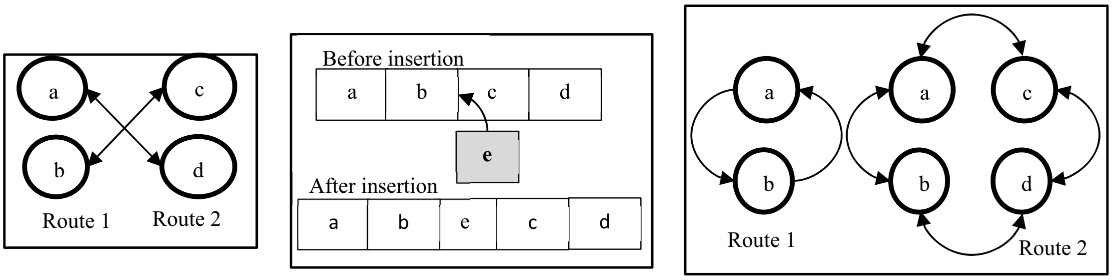
Solution construction in ACO is to optimize distance travelled by ants. These ants represented as the vehicles that completes the routes by choosing the best capacity and distance. The construction begins from a depot and the selection of the next customers are considered via distance and total customer capacity. Usually, each ant is assigned randomly for the first customer and will choose next customer. The optimization of vehicle distance with limited capacity with the total capacity of each customer can be visited only once for total route of journey with start and end at the same depot.

In this situation, the ants will select next customer via pheromone concentration values at the trails to move. Solution construction will keep on going until the ants reach the capacities and return to the same depot. The following solution, the next ants serve the remaining customers and the construction will be repeated until all customers are visited.

The construction of solution route will use all customers as candidates before each vehicle constructed their route. This mechanism needed because if the next customer is clustered before the solution construction, the solution route failed to identify a feasible solution especially if the position of the customer is scattered or random. To optimize this construction, heuristic method updates the pheromone to improve the route constructed by the current ants before the next ants start to construct a new solution. There are three basic heuristic methods suggested to be implemented in solution construction for neighbor creation in ACO, namely heuristic insertion, swap and reversion [10, 11].

3.2. Swap, Insertion and Reversion Methods

Heuristic swap method is the mechanism used to improve the cluster solution construction for distance optimization by swapping two customer positions from different routes [12, 13]. Swap process is a continuous process until it had no improvement for the solution or reaches maximum iterations. This mechanism has occurred if there are possibilities to improve the solution quality as shown in Figure 1(a). While heuristic insertion is a mechanism that choose a node and attempted to insert in any possibility's positions as shown in Figure 1(b). Insertion is to gain optimum distance by inserting a node into all nodes, one after another from the beginning of a route [14]. In addition, heuristic reversion is the mechanism used to adjust customer sequence by selecting customer sub-sequences and reverse the order of solution to be improved. This process started with the improved feasible route by reversing two customers. Then, followed by the next customer until the solution construction improved or reached final itteration. The distance optimization is based on the huge decrease for vehicle travelled distance illustrated in Figure 1(c). Figure 1 showed the methods of heuristic swap, insertion and reversion.



(a) (b) (c)

Figure 1. (a) Heuristic swap (b) Heuristic insertion (c) Heuristic reversion

4. Experiment

The data set used in this research is Christofides data which include clustered and random data. Data from C1 to C10 are random customer positioned data, while data from C11 to C14 are clustered customer positioned data. Furthermore, the parameter used in this research for ACO is 0.90 as initial pheromones with $\propto$ and β value are 5.00 and the evaporation rate of pheromone is 0.98 with 350 iterations [15]. The experiments are processed for five runs and the results displayed in Table 1 are the average distance from the runs. Firstly, the experiment is tested on ACO with one heuristic strategy, next ACO with two heuristic optimization strategy and finally, ACO with all three heuristic strategy. All optimization strategy run randomly which allow each iteration to choose one random optimization strategy. The results for this experiment are as in Table 1.

In original ACO, there are data that have possibilities for the vehicle to visit the same customer more than once in C5, C7, C9, C10, and C11. This condition occurs in ACO that combined heuristic swap method for C4, C5, C10 and ACO with heuristic insertion for C4, C5, C6, C10 and ACO with heuristic reversion in C4, C5, C9, C10. While ACO can randomly integrate two heuristic optimization methods for construction, for examples, swap and reverse or reverse and insert. There are possibilities for the vehicle to visit the same customers more than once in ACO with heuristic swap and reverse in C5 and ACO with heuristic swap and insert in C5, C10. There are no possibilities for the vehicle in ACO with heuristic reverse, insert and heuristic swap, reverse and insert to visit the same customers more than once and without exceeding the vehicle capacity.

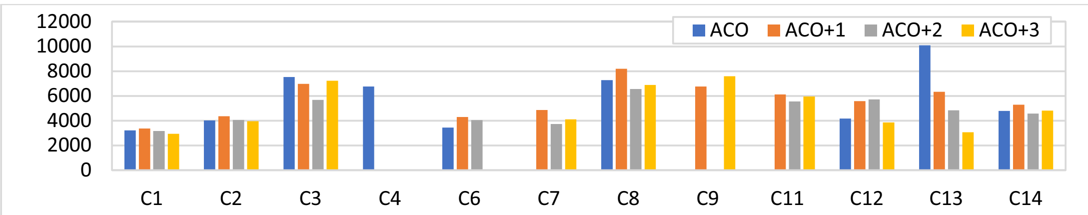
Figure 2 represents the solution construction of ACO with one heuristic optimffization. From Figure 2, C1 to C10 represent random customer positioned data, while the remaining C11 until C14 represent clustered customer positioned data. The result in ACO with heuristic optimization are proven to produce better results compared to using only ACO method. ACO with swap heuristic optimization method shows the most optimized distance for one random customer positioned data in C9. ACO with reverse method generates the best optimize distance for random data in C3, C7 and clustered data in

C11 while ACO with insert method shows the best optimize distance for random data in C1, C2 and clustered data in C12 and C13.

Table 1. Experimental results for solution construction in ACO with heuristic optimization

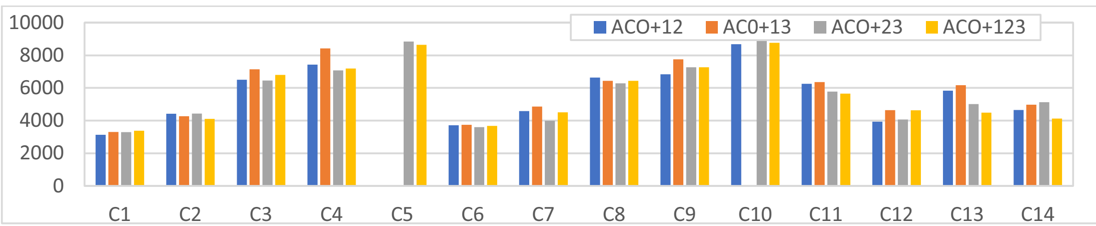
	ACO	ACO+1	ACO+2	ACO+3	ACO+12	ACO+13	ACO+23	ACO+123
C1	3214.02	3361.27	3156.89	**2932.03**	3142.08	3311.88	3301.54	3382.46
C2	4021.85	4358.23	4062.54	**3949.44**	4422.11	4273.41	4430.85	4110.98
C3	7522.14	6983.27	**5674.71**	7229.84	6502.30	7142.30	6449.22	6806.28
C4	**6751.92**	-	-	-	7434.28	8419.63	7079.98	7193.48
C5	-	-	-	-	-	-	8842.53	8642.14
C6	**3444.14**	4300.27	4042.96		3712.14	3743.75	3608.53	3675.42
C7	-	4857.35	**3724.99**	4102.54	4586.20	4867.00	3995.24	4510.58
C8	7274.30	8201.47	6557.37	6887.04	6641.09	6438.53	**6283.29**	6437.65
C9	-	**6750.12**	-	7591.95	6842.65	7756.65	7267.55	7273.63
C10	-	-	-	-	**8681.94**	-	9059.17	8766.22
C11	-	6113.16	**5545.79**	5952.87	6255.48	6358.90	5775.45	5653.17
C12	4180.65	5584.51	5710.33	**3861.16**	3935.54	4639.85	4071.44	4627.79
C13	10092.37	6328.30	4834.89	**3063.09**	5829.45	6171.65	5015.65	4486.19
C14	4793.28	5289.13	4579.99	4814.72	4659.11	4981.34	5131.67	**4128.22**

*Symbol – represent for invalid data
**Bold is for minimum distance
***1 is represent swap, 2 is represent reversion and 3 is insertion.



*1 is represent swap, 2 is represent reversion and 3 is insertion.

Figure 2. Solution construction in ACO with one heuristic optimization



*1 is represent swap, 2 is represent reversion and 3 is insertion.

Figure 3. Solution construction in ACO with two heuristic optimization

Unfortunately, the results showed in Figure 3 are not satisfactory using the integration between ACO with two heuristic optimization methods in term of distance optimization. However, the possibilities for the vehicle to visit the customers more than once can be minimised. ACO with insert and swap methods generate the maximised optimized distance for C10 (8681.94). The possibilities for the vehicle to visit the customers more than once only in C5, while ACO with insert and reverse methods had zero optimized distance, but the possibilities for the vehicle to visit the customers more than once is only in C5 and C10. There are zero vehicles visited the customers more than once in ACO with heuristic reverse and insert methods with maximised optimized distance in C8 (6283.29). In addition, ACO with heuristic swap, reverse and insert optimization produce minimised optimized distance in C14 (4128.22).

5. Conclusion

There are three different heuristic methods suggested by [4,12] for solution construction using ACO to solve CVRP. By implementing these three heuristics methods with ACO, insert method able to improve the cluster within the same routes compared to heuristic reverse method. . ACO with two heuristic methods such as swap and reverse methods, swap and insert methods and reverse and insert methods able to improve the results by reducing the possibilities for the vehicles to visit the same customer more than once. While ACO with random heuristic reverse and insert methods and ACO with random heuristic swap, reverse and insert methods can improvise the results by minimizing the total travel distances without visiting the same customer more than once. It is important to choose the best heuristic optimization for CVRP case study. In future work, this paper suggests to conduct heuristic removal aligned with CVRP constraints.

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