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Improvement heuristic method for capacitated vehicle routing problem

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ABSTRACT

This study reports on the use of improvement heuristic for Capacitated Vehicle Routing Problem (CVRP). The problem is restricted to a single capacity constraint in order to distribute goods to the customers. The proposed improvement methods are aimed at relocating customers between different routes, starting from an initial feasible solution. The results are compared on three types of data i.e. clustered, random and random-clustered to see the performance of proposed method.

Keywords: Heuristic; Vehicle Routing Problem; Capacitated Vehicle Routing Problem; Clustered; Random; Random-Clustered.

1. INTRODUCTION

Nowadays, exchange of goods in the world is growing rapidly and it is caused by the globalization of economy. It is very important to use computer-aided systems for the planning of the transports since there are limited commodities and transportation resources, high planning complexity and the increasing cost pressure through the strong competition between logistics service providers. The operational planning of trucks or other specialized transportation vehicles is an important task in this context. These optimization tasks are called Vehicle Routing Problems (VRP). VRP is an optimization problem that used to design an optimal route for a group of vehicles subject to a set of constraints in order to give service to a set of customers. Minimizing the total route cost is the main objective of VRP [1].

VRP problems can be classified creating a taxonomy or creating a generalized framework that summarizes the existing models, the objectives pursued and the theories associated with the analysis of the problem [2]. Furthermore, the VRP can be classified into many components or types since it has wide variants. One of its components is Capacitated Vehicle Routing Problem (CVRP).

In general, a CVRP considers equal capacities for all vehicles; although in real life vehicle fleet with different capacities can be used to solve the delivery problem [3]. A number of variations of CVRP are also available such as considers multiples depot instead of one and considers time window constraint defining time frames when a customer can be serviced. The simplest form of CVRP is considering one depot and several vehicles with equal capacity which been studied here.

2. CLASSICAL HEURISTICS FOR VEHICLE ROUTING PROBLEM (VRP)

Classical heuristic methods have limited exploration of the search space but can still produce good quality solutions within modest computing times [4]. Laporte and Semet in [5] have classified classical heuristic into three main categories, which are constructive heuristics, two-phase heuristics and improvement heuristics.

Constructive heuristics build the feasible solutions gradually. At the same time, this heuristic keeps an eye on the solution cost. In two-phase heuristics, the problem is decomposed into its two natural components; i.e. clustering of vertices into feasible routes, and the actual route construction. There are two methods, by which this is done. They are cluster-first route-second, and route-first cluster-second.

Improvement heuristics are normally applied to improve a feasible solution obtained by using other methods. The heuristics will search for the best improvement solution if possible. Then, the solution is updated and the search for a new improved solution is repeated until no more improvement is found or stopping condition is met. Improvement heuristics can be divided into two; i.e. single-route improvement and multi-route improvement. The terminologies of both single-, and multi-route improvement were found in [5] which gave the same meaning of intra- and inter-route improvement. The intra-route improvement performs changes to one route at a time such as permute the customers within a route, while the latter involves exchanging and moving customers between two or more routes. A more complete survey on intra- and inter-route improvement can be found in [6].

3. FORMULATION OF CVRP MODEL

The single depot CVRP model has the objective function, decision variables, constraints and parameters, which are written as follows.

The parameters involved:

n The number of customers
m The vehicles number
M The total number of vehicles
Q_m The capacity of vehicle *m*
q_i The demands of each customer *i*
$C_{i,j}^m$ The travel cost of vehicle *m* from customer *i* to customer *j*

Decision variables:

$$X_{ij}^m = \begin{cases} 1, & \text{If vehicle } m \text{ travels from customer } i \text{ to customer } j \\ 0, & \text{Otherwise} \end{cases} \tag{1}$$

The objective of the problem:

minimize $\sum_{m=1}^{M} \sum_{i=0}^{n} \sum_{j=0}^{n} C_{i,j}^m X_{i,j}^m$ (2)

subject to:

$$\sum_{m=1}^{M} \sum_{i=0}^{n} X_{i,j}^m = 1 \text{ for all } j = 0,1,2,\dots,n \tag{3}$$

$$\sum_{j=0}^{n} q_j \left(\sum_{i=0}^{n} X_{i,j}^m \right) \le Q_m \text{ for all } m = 0,1,2,\dots,M \tag{4}$$

$$\sum_{j=1}^{n} X_{0,j}^m \le 1 \text{ for all } m = 1,2,\dots,M \tag{5}$$

$$\sum_{i=1}^{n} X_{i,0}^m \le 1 \text{ for all } m = 1,2,\dots,M \tag{6}$$

From the CVRP model above, the decision variables are written as equation (1) and the objective function (2) is to minimize the total cost involving by all the vehicles used. The constraint in (3) shows that, all customers will be served. The total demand of the customers does not exceed the vehicle capacity are given by equation (4). Lastly, equation (5) and equation (6) state that each vehicle originates from the depot, and goes back to the depot respectively.

3.1 Description of improvement heuristic.

The proposed method can be described as follows:

Step 1. Consider that we have two different routes and define both routes as R1 and R2. Both routes are an initial solution that is obtained through Sequential Insertion Method [7].
Step 2. For instance, R1 consists of three nodes (customers) while R2 has two nodes. We denote nodes for RI as nodes A, B and C (0-A-B-C-0) while R2 has nodes E and F, (0-D-E-0).
Step 3. Select one node randomly from any routes, for example, node B is randomly selected from its route.
Step 4. Detect the route of the node. For example, node B is detected from R1. Remove that node from its original route. Then, R1 becomes 0-A-C-0.
Step 5. Then, node B will be inserted randomly into R2. In R2, B will be tested for all possible routes. For instance, R2 can be 0-B-D-E-0, 0-D-B-E-0 or 0-D-E-B-0.
Step 6. Then, based on the new route formed from each of the possibility test, calculate their total distances in order to choose which route give the least cost.
Step 7. The routes that have least cost of distance travelled from step (vi) will be chosen as the best improvement routes.

The proposed method above will be used to improve an initial solution for CVRP which been studied by Fei [7]. The cost is corresponding to the total distance travelled by all vehicles. The distance between two nodes, i.e. represents 2 different customer's locations, which is i and j in a Cartesian plane, as an example, (x_i, y_i) and (x_j, y_j) is computed by using the Euclidean distance that is derived from the Pythagoras Theorem as follows:

$$d_{i,j} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2} \qquad (7)$$

4. RESULTS AND DISCUSSIONS

In this study, we used the benchmark data for CVRP provided by Solomon [8], which involve 100 customers with a single depot. There are three different sets of data, namely, random, clustered and random-clustered data. Since the study focus on the capacity constraint only, then these data with imposed capacity are taken for comparison and analysis. Random, clustered or random clustered are referring to the distribution of customers location around the depot.

The heuristic were coded in the C++ programming language. The algorithm involves random code in which the result will be different for every run. Therefore, for each maximum capacity, we run for 5 times and take the average of 5 solutions, which are C1, C2, C3, C4, C5 for clustered, R1, R2, R3, R4 and R5 for random and also RC1, RC2, RC3, RC4 and RC5 for random-clustered data. As mentioned, the improvement solutions are done based on the initial solution for the same data, which is obtained from Fei [7]. The results presented were based on number of routes and average number of customers in one route.

4.1 Clustered Data

In Table 4.1, there is a comparison for clustered data between four different capacity constraints, which are 100, 150, 200 and 250. Table 4.1 shows that when the value of vehicle capacity increases, the average number of customer increases too but the number of routes and the total distance travelled by the vehicle decrease. This is because the vehicle with greater capacity is capable to bring more goods or items to be distributed to the customers. Therefore, all the customer demands can be satisfied with fewer routes and the average number of customer for each routes increase.

Table 4.1: Initial solution for clustered data

Maximum Capacity (units)	Number of Routes	Average Number of Customer	Total Distance (units)
100	19	5	3454.6997
150	13	8	2829.8615
200	10	10	2440.2075
250	8	13	2143.7548

Table 4.2 shows that improvement on the current solution can be done by relocating randomly a customer to the other route which are chosen randomly too. The improvement solutions by using inter-route improvement heuristic algorithms and the average of total distance for each vehicle constraint are given in Table 4.2 below. The average total distance for all types of data decreases when the capacity constraint increases.

4.2 Random Data

Table 4.3 shows the initial solutions that are acquired for random data, which include the number of routes, average number of customer and the total distance travelled by the vehicle. The increasing values of capacity constraints will reduce the number of vehicle routes formed by increasing the number of customers in a route.

From Table 4.3, 250 units of maximum capacity will result in lowest total distance travelled compared to maximum capacity of 100 units.

Table 4.2: New improvement solution for clustered data

Maximum Capacity (units)	Random results	Number of Routes	Average Number of Customer	Total Distances (units)
100	C1	19	5	3434.5997
	C2	19	5	3419.6427
	C3	19	5	3442.6057
	C4	19	5	3444.1487
	C5	19	5	3438.1468
	Average Total Distance			**3435.8287**
150	C1	13	8	2814.1777
	C2	13	8	2797.2025
	C3	13	8	2810.2145
	C4	13	8	2817.0552
	C5	13	8	2790.5045
	Average Total Distance			**2805.8309**
200	C1	10	10	2401.5915
	C2	10	10	2424.2075
	C3	10	10	2415.8094
	C4	10	10	2425.5157
	C5	10	10	2404.1525
	Average Total Distance			**2414.2553**
250	C1	8	13	2121.3519
	C2	8	13	2103.4428
	C3	8	13	2124.7548
	C4	8	13	2125.8278
	C5	8	13	2116.6435
	Average Total Distance			**2118.4042**

Table 4.3: Initial solution for random data

Maximum Capacity (units)	Number of Routes	Average Number of Customer	Total Distance (units)
100	15	7	2534.6823
150	10	10	2014.9593
200	8	13	1772.0627
250	6	17	1514.6816

The improvement solution of random data by using the proposed method and the average of total distance for each vehicle constraint are given in Table 4.4.

Table 4.4: New improvement solution for random data

Maximum Capacity (units)	Random result	Number of Routes	Average Number of Customer	Total Distances (units)
100	R1	15	7	2514.9843
	R2	15	7	2495.9893
	R3	15	7	2509.1863
	R4	15	7	2504.2683
	R5	15	7	2503.6763
	Average Total Distance			**2505.6209**
150	R1	10	10	1991.7063
	R2	10	10	1989.4643
	R3	10	10	1998.8013
	R4	10	10	1997.3023
	R5	10	10	2009.9443
	Average Total Distance			**1997.4437**
200	R1	8	13	1745.1367
	R2	8	13	1748.8677
	R3	8	13	1753.6777
	R4	8	13	1760.8817
	R5	8	13	1734.6647
	Average Total Distance			**1748.6457**
250	R1	6	17	1499.0406
	R2	6	17	1493.4206
	R3	6	17	1503.3686
	R4	6	17	1505.6256
	R5	6	17	1497.5166
	Average Total Distance			**1499.7944**

4.3 Random-Clustered Data

The initial solution for random-clustered data, which include the number of routes, average number of customer and the total distance travelled by the vehicle are shown in Table 4.5.

Table 4.5: Initial solution for random-clustered data

Maximum Capacity (units)	Number of Routes	Average Number of Customer	Total Distance (units)
100	18	6	3735.3577
150	12	8	3206.4380
200	9	11	2808.5700
250	7	14	2393.3960

Table 4.6 showed the improvement solution of random-clustered data using the proposed method.

Table 4.6: New improvement solution for random-clustered data

Maximum Capacity (units)	Random result	Number of Routes	Average Number of Customer	Total Distances (units)
100	RC1	18	6	3687.9237
	RC2	18	6	3704.5517
	RC3	18	6	3700.0027
	RC4	18	6	3696.0007
	RC5	18	6	3683.3577
	Average Total Distance			**3694.3673**
150	RC1	12	8	3190.6270
	RC2	12	8	3188.4100
	RC3	12	8	3162.4740
	RC4	12	8	3134.2521
	RC5	12	8	3185.7010
	Average Total Distance			**3172.29282**
200	RC1	9	11	2781.7570
	RC2	9	11	2789.3340
	RC3	9	11	2771.8410
	RC4	9	11	2767.2720
	RC5	9	11	2775.0280
	Average Total Distance			**2777.0464**
250	RC1	7	14	2359.7960
	RC2	7	14	2351.9940
	RC3	7	14	2322.8210
	RC4	7	14	2364.2220
	RC5	7	14	2327.6940
	Average Total Distance			**2345.3054**

4.4 Results Comparison

Some comparisons can be made for all the three types of data obtained from the improvement heuristics. This comparison will includes the maximum capacity, the number of routes of vehicle, the average number of customers, the total distance travelled and the improvement percentage made. The following Table 4.7 and Table 4.8 present the comparison results.

From Table 4.7, we can see that the maximum capacity 250 shows the largest percentage improvement in all types of data. Therefore, we use results of 250 of maximum capacity to do other comparison as shown in Table 4.8. However, for random data, the improvement had not been made for capacity constraints of 150 by using inter-route improvement heuristic compared to the previous result by [7]. Overall, the highest improvement is from the capacity constraint of 250 in random-clustered data which is 4.83% while the lowest improvement which is 1.32% from random data with capacity constraint of 100.

Comparisons on three types of data with 250 maximum capacity based on their initial solution are presented in Table 4.8. In summary, the total distance travel by the vehicle from previous data is decreased. Random-clustered data has the highest improvement percentage of 4.83 followed by clustered data and random data.

Table 4.7: Comparison of solutions between initial solution [7].

Type of Data	Maximum Capacity (units)	Previous result by Fei (2015)	Current Result by Improvement	Improvement percentage (%)
Clustered Data	100	3548.7017	3419.6427	3.64
	150	2885.6695	2790.5045	3.30
	200	2499.6315	2401.5915	3.92
	250	2200.4298	2103.4428	4.41
Random Data	100	2529.4894	2495.9893	1.32
	150	1913.1750	1989.4643	-3.94
	200	1773.7181	1734.6647	2.20
	250	1556.3250	1493.4206	4.04
Random-Clustered Data	100	3815.5387	3683.3577	3.46
	150	3284.8540	3134.2521	4.58
	200	2867.8790	2767.2720	3.51
	250	2440.7930	2322.8210	4.83

Table 4.8: Comparison of solutions between three different types of data.

	Clustered Data	Random Data	Random-Clustered Data
Maximum Capacity (units)	250	250	250
Number of Routes (units)	8	6	7
Average number of Customers	13	17	14
Previous Total Distance by Fei (2015)	2200.4298	1556.325	2440.793
Current Total Distance by Improvement	2103.4428	1493.4206	2322.821
Improvement Percentage (%)	4.41	4.04	4.83

5. CONCLUSIONS AND FUTURE WORK

There are some conclusions that can be drawn for this problem. Firstly, the value of capacity constraints for each vehicle affects the number of routes and total travelled distance. The higher the capacity of vehicles, the smaller the number of routes and the total distance travelled by the vehicles. The computational results acquired by using C++ programming language showed that random data has the shortest total distance travelled compared to clustered and random-clustered data with the same value of capacity constraints. Besides, inter-route improvement heuristic method concerns on the selection of shortest distance route by relocating the route of vehicles. This method is more beneficial to random-clustered data that produced the highest improvement solution.

This study only focuses on how to generate better solution by using an improvement heuristic method of CVRP, which involves one neighborhood only. So, it is recommended to carry out other heuristic methods such as intra-route improvement, 2-opt, 3-opt and 3-opt improvement for further research. It is also suggested to use other metaheuristics method such as Variable Neighborhood Search (VNS) Algorithm.

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