



Assignment Algorithm for Multi Depot Vehicle Routing Problem Using Genetic Algorithm

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Abstract

Context: The challenge is to find an efficient way to schedule vehicle individually so that the vehicle drive in most efficient way and the package arrives at the customer in time. **Objective:** Solving Multi-Depot Vehicle Routing Problem (MDVRP) is difficult especially with precise methods like bond and branch, branching and cut algorithms to efficiently and effectively tackle the problem, this research aimed at proposing an assignment that minimize distance and time of MDVRP and optimized MDVRP using Heuristics Genetic algorithms. Thus, in this paper, we presented an assignment algorithm for MDVRP that minimizes the travel distance and makes package arrives at the customer in time for MDVRP. **Method:** Our algorithm assign closest customer to each depot and requires each depot to attract one customer every time until all customers are assigned. The algorithm uses shortest path (Dijkstra) algorithm to identify closest customer to each depot and assign it to that depot and then for each depot closest customer to the last assign customer is identified and assign it to that depot. The proposed assignment algorithm was implemented in a classical MDVRP. **Results:** the average travel distance acquired for S1(P01 to P23) form the proposed assignment algorithm was 2522.30km and that from the existing literature was 2694.69km. This shows that the proposed assignment algorithm minimized travel distance and travel time drastically which proves the effectiveness of GA in solving MDVRP.

Keywords: Multi-depot; vehicle routing; Assignment algorithm; Genetic Algorithm.

1. Introduction

Multi-Depot Vehicle Routing Problem (MDVRP) is a combinatorial optimization problem that catches so many researchers' attention for its real-life application. MDVRP is a well-known Vehicle Routing Problem (VRP) in which customers are served from different depots. This form of problem has many applications in the transport, distribution and logistics industries in their real life (Eiben, 2004). The MDVRP can be seen as a question of clustering because its production is a collection of vehicle schedules clustered by the depot. This definition implies an approach of clustering customers and scheduling the vehicles over each cluster. Multi Depot,

providing a collection of customers that must be served by multiple deposits.

Vehicle Routing Problem is usually aimed to assign each customer to the appropriate depot based on the distance from each customer to the depot, and also finds optimal service tour, assignment (clustering) of customers to appropriate depot is much significant, which requires an efficient way to deal with. The consequences of poor planning are costly, and a decision-maker often needs to fine-tune the system to ensure that the customer's needs are met in a timely and distance-efficient manner (Masum, Shahjalal, ..., & 2011.). MDVRP was solved using problem decomposition techniques where Cooperative Co-

Evolutionary Algorithm (CoES) for Multi-Depot Vehicle Routing Problem was proposed by (Bernardes De Oliveira, Enayatifar, Sadaei, Gadelha Guimarães, & Potvin, 2015), decomposing the problem into sub-problems together with individuals from certain groups come together to find a complete solution to the original problem. MDVRP was also solved and optimized using Genetic Algorithm (GA) by (Surekha, Programming, & 2011.), Customers are grouped to their nearest depots by distance, and then routed using the Clarke and Wright saving method. The work carried by (Biswas, 2017; Singh, Ganapathy, of, & 2019) presented different genetic approaches, methods and operators, commonly used in solving MDVRP.

The review conducted indicated that most of the algorithms designed were inadequate in using efficient assignment algorithm, efficient genetic operators and sophisticated local search that will solve MDVRP at minimal travel time and travel distance. Perhaps, the reviewed researches and their drawbacks stressed the need for an efficient assignment algorithm (an algorithm that will cluster customer to various depots), local search and effective genetic operators since the efficiency of MDVRP largely depends on the heuristics employed in assume distribution (clustering) of customers to depots. This research proposed an assignment algorithm which solved the problem at minimal travel distance and travel time and help vehicles to find routes such that all the customers are visited and scheduled efficiently. An efficient assignment algorithm will present an organization with several branches a means to deliver goods or services to their customers in a minimized travel distance, time and cost. Clustering customers and servicing them in a convenient approach will cut down the price of goods. This will contribute in making good planning for the transportation fleet and make transportation material more utilized.

2. Motivation and Related Works

The problem of vehicle routing (VRP) was an open issue, and the front line of the algorithms for operational research and optimisation. The multi-depot vehicle routing problem (MDVRP) also received further attention from scholars as a variant of the VRP (Shi, Lv, Hu, & Han, 2020). The work of (Zunic, Donko, & Buza, 2020) provides an innovative modular adaptive data-driven approach to the solution of real-world vehicle routing problems (VRPs) in the logistics sector. The research consists of two primary units: I an advanced multi-step algorithm for effective and fully feasible logistics solution of the VRPs, and (ii) an optimized framework for adapting and setting the proposed algorithm's parameters and constants.. (Wang et al., 2019) Adopted ACO to solve MDVRP variants, such as multi-objective MDVRP and time-window MDVRP. (Alinaghian, Omega, & 2018) proposed a hybrid algorithm

consisting of an efficient large-scale neighbourhood's searching and variable neighbourhood searching to solve this problem where each vehicle's cargo space has several components and each compartment is limited to a single product category. (Zhao, Leng, & Zhang, 2019) stated that the problem of routing multi-depot vehicles (MDVRP) has also attracted more attention from scholars.

Several research works such as journals, books, conference proceedings, Document form website, were thoroughly investigated in an attempt to identify the performance measure for measuring the effectiveness of MDVRP. The criterion used to measure service delivery effectiveness depends on the type of service offered. While minimizing total costs is an important criterion for MDVRP, criteria such as minimizing customer inconvenience, reducing fuel consumption, minimizing fleet size, minimizing execution costs and minimizing response time may be equally important if not more important.

The problem with MDVRP is to allocate the demand to each depot, provided that the supply of each depot is not exceeded and the order in which vehicles visit customers is arranged. (Surekha, Programming, & 2011.) Solved and optimized MDVRP via GA. The customers are grouped by distance to their nearest depots and then routed with the saving method of Clarke and Wright. A collection of five separate benchmark instances of Cordeau (p06, p05, p04, p03, p02 and p01) were experimented using MATLAB R2008b software from the University of Malaga, Spain's online tool. The obtained results were analysed in with respect to the optimal distance, average distance, depot's route length, optimal route, computational time as well as number of vehicles. Shows that GA efficiency is feasible and efficient for solving the vehicle multi-depot routing problem. The work carried by (Biswas, 2017; Singh, Ganapathy, of, & 2019) offered dissimilar genetic approaches, methods and operators, commonly used in solving MDVRP.

The above researches and their drawbacks stressed the need for an efficient assignment algorithm (an algorithm that will assign customers to different depots), local search and effective genetic operators, since MDVRP's efficiency largely depends on the heuristics used to assign depots to customers.

3. Methodology of the Proposed Assignment Algorithm

The proposed assignment algorithm allows each depot to attract single customer at a time before the assignment of all customers. The algorithm rule uses shortest path Algorithm rule to spot closest customer to every depot and assign it thereto depot so for every depot closest customer to the last assign customer is known and assign it to that depot, the situation continues till all the

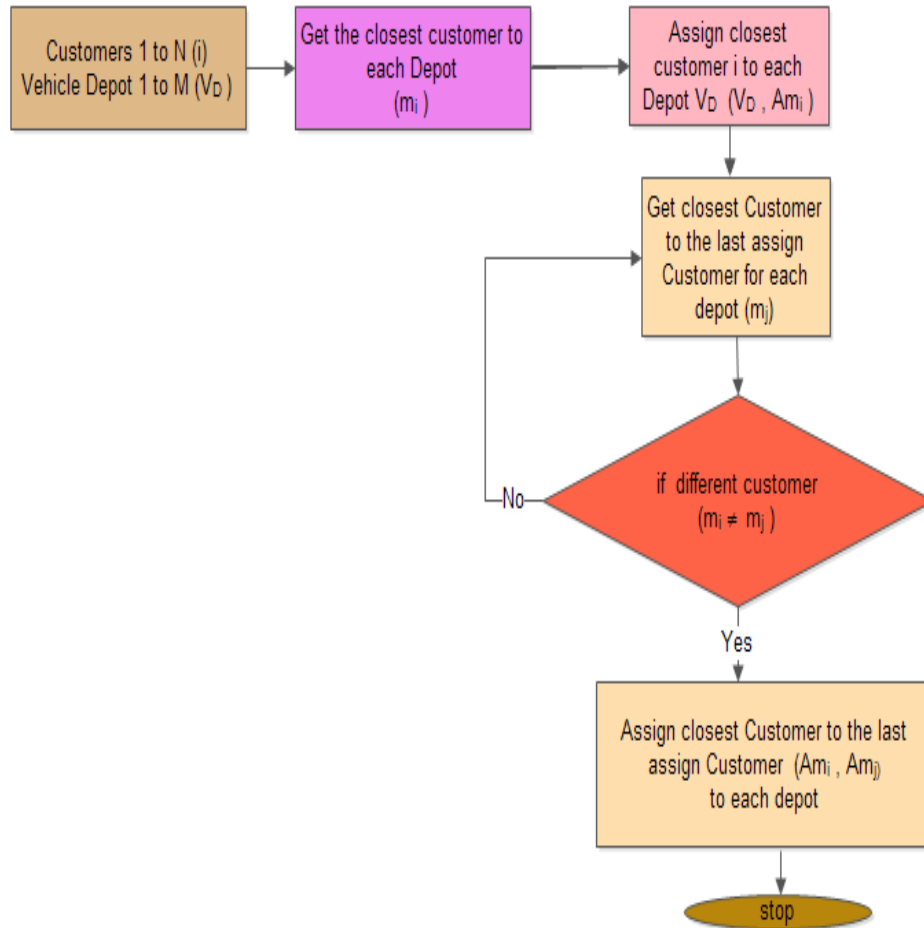


Figure 2: Flowchart of the proposed assignment algorithm.

The algorithm uses shortest path algorithm to identify closest customer to each depot and assign it to that depot and then for each depot nearest customer to the last assign customer is known and assign, the scenario continues until all the customers are assign to the appropriate depot. The proposed assignment algorithm on figure 2 allows each depot to attract single customer

at a time before the assignment of all customers. This algorithm was designed based on the proposed flowchart of the proposed assignment algorithm. Figure 2 illustrate the proposed assignment algorithm and Listing. 2 described it.

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Output : Assignment of Customers to the depot
Input: Customers 1-N and Depot 1 –M
Step1: AssignCustomers(Vc, VD, A)
Step2: for i=1 to N do // foreach customer i
        //Rule 1: Assign closest customer to each depot
Step3: mi=getclosestcustomer(VD, i);
Step4: insert(VD, Ami);
//Rule 2: Assign closest customer to the last assign
customer
Step5: foreach VD= 1 to m
Step6: while(i≠0)
Step7: mi= getclosestneighbour(Amj, i );
Step8: if (mi ≠ mj) then // different customers
Step9: insert(Amj, Ami);

```

Listing 2: Proposed Assignment Algorithm

The method of assigning customer to the depot is detailed in listing 4 of the proposed algorithm. The route starts with the set of VC customers, the set of VD depots and the set of arcs. In Line 3 the nearest customer m_i to depot VD is selected in compliance with rule 1 and placed in line 4 to the assignment cluster Am_i of depot VD. The algorithm checked to see if there are still customers to be allocated to the depot. If there are, the nearest neighbor to last assigned customer i is identified as customer Am_i (Line 7) and the nearest customer to the last assign customers j , identified as m_j , is chosen in compliance with rule 2, the customers are compared in Line 8. If pair of customers is dissimilar ($m_i \neq m_j$), customer i is also included in the allocation c Am_i 's category of customer m_j (Line 9). In line 14 the assignment groups are returned after all customers have been processed. The whole algorithm's complexity is in (the worst case) $O(d+c^2)$, c is the number of customers, and d is the number of depots

4. Implementation of the Proposed Algorithm.

The research work was implemented using MATLAB. Random population known as the chromosome were generated and evaluated using fitness function which permits the allocation of reproductive opportunities so that those chromosomes that are

better solution to the target problem have more chances of reproduction than

Those chromosomes that are inferior solutions. Typically, the integrity of a solution with respect to the current population is determined. The population was partitioned using an Island strategy (Island Evolution) to allow parallel computing to take its count, the population was broken down into category of 16 individual bits, the decomposition approach employed, grouped closest customers to the same depot based on the scenario of the proposed algorithm and allows solving each sub problem in parallel.

5. Benchmark Specification.

The proposed assignment algorithm for MDVRP was assessed through the 33 MDVRP standards (benchmark instances) extracted from (Bernardes De Oliveira et al., 2015; Cordeau, ..., & 1997, n.d.; Vidal, Crainic, Gendreau, & Prins, 2014). These standards were grouped into S1 (P01–P23) and S2 (P24–P33), each instance have an assortment of sizes as tabulated in the Table 1 below. In this research work both group S1(P01-P23) and S2(P24-P33), range of customers 50 to 360 were used for the experiment and each benchmark instance was run 5 times using the parameters specified in Table 1 below in order to

extract the mean values for the minimum travel distance and travel time of the experiment.

Table 1: Specifications of Benchmark Instances (S1)

Parameters/Instances	Total no. of customers(N)	Total no. of Depots(M)	Capacity of each Vehicle(Q)
P01	50	4	80
P02	50	2	160
P03	75	3	140
P04	100	8	100
P05	100	5	200
P06	100	6	100
P07	100	4	100
P08	249	14	500
P09	249	12	500
P10	249	8	500
P11	249	6	500
P12	80	5	60
P13	80	5	60
P14	80	5	60
P15	160	5	60
P16	160	5	60
P17	160	5	60
P18	240	5	60
P19	240	5	60
P20	240	5	60
P21	360	5	60
P22	360	5	60
P23	360	5	60

Table 1 represent benchmark specification for standard one (S1) that is P01 to P23 with the total number of customers (N),

number of depots(M) and capacity of each vehicle(Q) for each instance. Table 2 depict benchmark specification for S2.

Table 2: Specifications of Benchmark Instances (S2).

Parameters/Instances	Total no. of customers(N)	Total no. of Depots(M)	Capacity of each Vehicle(Q)
P24	1	48	200
P25	2	96	195
P26	3	144	190
P27	4	192	185
P28	5	240	180
P29	6	288	175
P30	1	72	200
P31	2	144	190
P32	3	216	180
P33	4	288	170

Table 2 characterize benchmark specification for standard one (S1) which are P24 to P33 with the total number of customers(N), number of depots(M) and capacity of each vehicle(Q) for each instance.

6. Result Analysis

This section discuss on the analysis of the result to determine the extent to which the parameters were improved, the mean values of the result obtained for the table 3 were compared with the work done by [7] that is (Co-Operative co-Evolutionary Strategy COES) in order to validate the proposed algorithm.(GA $\lambda = \mu$) result

Table 3: Comparison of proposed of GA-MDVRP result and CoES result for S1

Instance	Proposed GA – MDVRP			CoES			
	M	N	Q	Mean Values		Mean Values	
				Time(s)	Distance	Time(s)	Distance
P01	4	50	80	0.80	473.96	1.00	576.87
P02	2	50	160	0.20	453.93	0.50	475.06
P03	3	75	140	1.00	598.05	2.50	643.57
P04	8	100	100	169.91	973.54	189.70	1011.42
P05	5	100	200	18.20	749.73	26.60	752.39
P06	6	100	100	67.43	768.35	77.30	877.86
P07	4	100	100	21.56	898.89	24.20	893.36
P08	14	249	500	700.26	3629.52	803.40	4474.23
P09	12	249	500	503.63	3312.31	513.30	3904.92
P10	8	249	500	702.96	3211.32	719.00	3680.02
P11	6	249	500	372.91	3495.48	396.20	3593.37
P12	5	80	60	0.76	1244.57	0.90	1381.95
P13	5	80	60	0.00	1280.61	0.00	1381.95
P14	5	80	60	0.00	1296.08	0.00	1360.12
P15	5	160	60	91.92	2234.00	107.00	2549.65
P16	5	160	60	6.50	2335.62	8.20	2572.23
P17	5	160	60	13.62	2414.25	14.70	2733.80
P18	5	240	60	410.20	3664.45	429.10	3781.66
P19	5	240	60	67.70	3780.07	72.60	3827.06
P20	5	240	60	186.37	4035.93	190.20	4096.86
P21	5	360	60	512.78	5561.50	554.90	5668.97
P22	5	360	60	204.05	5601.98	214.00	5708.78
P23	5	360	60	511.36	5998.69	529.30	6159.90
			Average	198.44	2522.30	211.98	2694.69

Table 3 depict the result of comparison between the proposed GA-MDVRP and that of (Bernardes De Oliveira, Enayatifar, Sadaei, Gadelha Guimarães, & Potvin, 2015), average values

were computed and the results shows that in proposed GA-MDVRP there is significant reduction of travel distance and travel time.

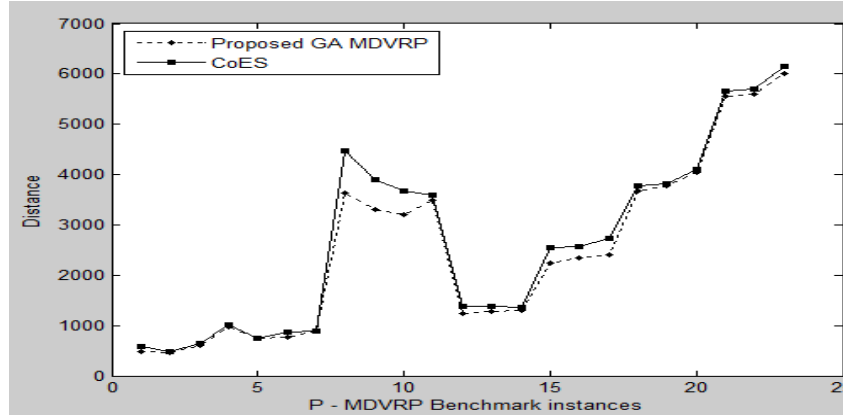


Figure 4: Travel distance for S1 benchmark instances of GA-MDVRP compared with CoES

Figure 5 indicated the benchmark instances S1(P01 to P23) against Travel Distance for GA-M DVRP and CoES, this shows

the travel distance was drastically minimized in contrast with the Cooperative co-Evolutionary Strategy(CoES).

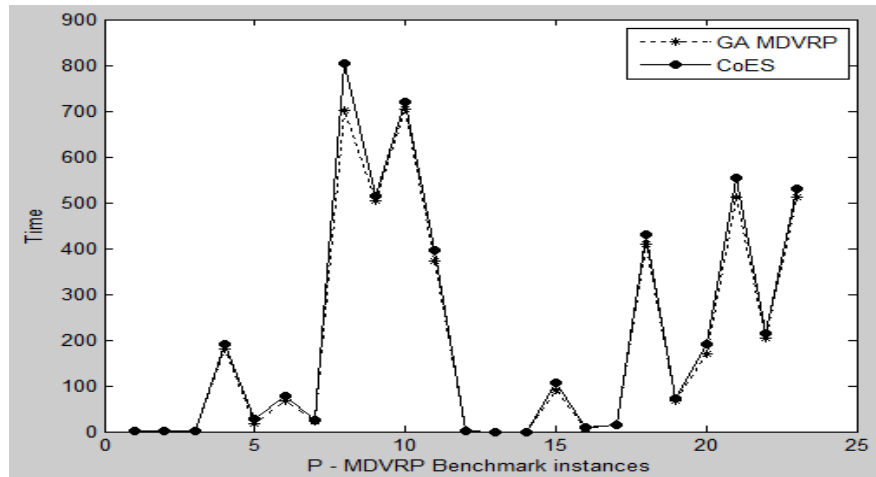


Figure 5: Travel time of GA-MDVRP compared with CoES for S1

Figure 4 shows a graph of benchmark instances P01-P23 against the travel time, in the graph computation time of GA-MDVRP

broadly minimized compared to travel time of CoES from the literature.

Table 4: Comparison of GA-Mdvrp result and Coes result for S2

Instance	Proposed GA- MDVRP			CoES			
	M	N	Q	Mean Values		Mean Values	
				Time(s)	Distance	Time(s)	Distance
P24	1	48	200	0.00	769.16	0.00	849.17
P25	2	96	195	529.70	1033.71	630.80	1271.39
P26	3	144	190	100.98	1562.89	123.60	1768.13
P27	4	192	185	433.42	1944.76	580.80	2057.50
P28	5	240	180	223.38	2153.20	321.00	2362.75
P29	6	288	175	529.19	2538.26	724.40	2690.01
P30	1	72	200	0.45	959.646	0.60	1070.85
P31	2	144	190	205.39	1598.65	254.00	1650.96
P32	3	216	180	447.54	2050.66	652.50	2160.76
P33	4	288	170	306.63	2588.62	472.80	2844.32
Average				277.67	1719.96	376.05	1872.58

Table 4 describe the result of comparison between the proposed GA-MDVRP and that of (Bernardes De Oliveira, Enayatifar, Sadaei, Gadelha Guimarães, & Potvin, 2015) for S2 benchmark

instances, average values were computed and the results shows that in proposed GA-MDVRP travel distance and travel time were minimized.

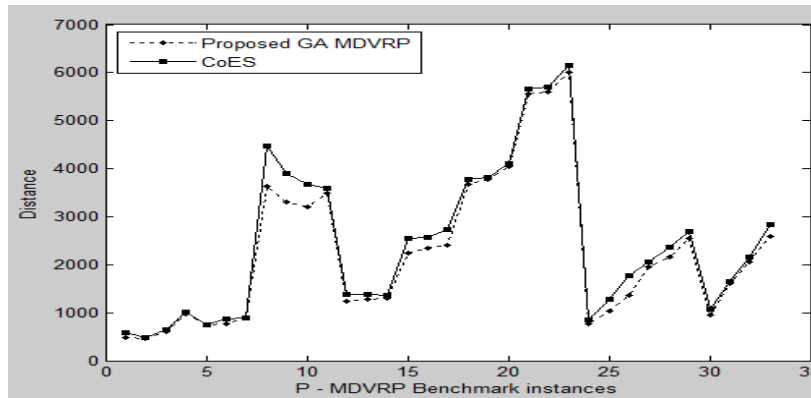


Figure 6: Travel distance of GA-MDVRP compared with COES for all the benchmark instances (S1 and S2)

Figure 6 indicated all the benchmark instances P01 to P33 against Travel Distance for GA-MDVRP and CoES, this shows the travel distance is drastically minimized in contrast with the Cooperative co-Evolutionary Strategy(CoES). This proves the effectiveness of GA since it improved the solution quality for a number of instances.

7. Conclusion

This research work improved the effectiveness of Multi Depot Vehicle Routing Problem through minimization of travel distance and travel time; this was achieved through the

assignment Algorithm proposed. The efficacy of the proposed Assignment Algorithm was implemented in classical MDVRP and tested in the MATLAB R2007b environment by a set of thirty three different Cordeau's and Oliveira's benchmark instances namely p01-p23 and p24-p34 known as S1 and S2 respectively. Each benchmark instances were run five times where mean value was taken for comparative analysis. From the experiments performed, it was found that GA's efficiency was exceptional, and the computational time showed that optimization using GA is much faster, and the reduced travel

time proved that GA was good at finding smaller gene subsets and better accuracies in finding a solution to the multi-depot vehicle routing problem.

In the future, attempts will be made to place more rational constraints on the problem nature and new approach to attempt large size real-time problems will be developed.

Fitness function needs to be more sophisticated than the simple one used right now to ensure a final compact subset every time.

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