



A Genetic Clustering Algorithm for Multi-Depot Vehicle Routing

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Abstract

Multi Depot Vehicle Routing Problem (MDVRP) is a well-known real-life problem with many real life applications in the areas of transportation, distribution, and logistics. MDVRP is an extension of classical Vehicle Routing Problem (VRPs) with more than one depot, applicable to organizations which have several branches and each branch aimed at delivering goods or services to their customers simultaneously. This research work is aimed at proposing an efficient clustering algorithm for Clustering customers to an appropriate depot and was implemented in a classical MDVRP in order to quantify how travel distance and time are minimized. Genetic Algorithm (GA) was used to optimize the overall process because of its stochastic nature, efficiency, parallelism feature in solving combinatorial optimization problems. The main difference between the existing algorithm and the proposed algorithm is seen clearly in the rule 1 and 2 of the algorithm, the existing algorithm identified The closest depot to the customer and make an assignment then the closest depot to the closest neighbor node while the proposed algorithm identified closest customer, assign it to the depot and, then assign closest customer to the last assign customer. A simulation model for the algorithm was developed using MATLAB R2007b. The manual summation of the whole 33 benchmark instances of the result was conducted in order to obtain the optimal route for the existing algorithm which gives a total travelled distance of 80831.84 km and travelled time of 8635.1s; while total travelled distance for the proposed Genetic Clustering Algorithm was 75312.39 km and travelled time of 7340.8s. The result obtained from the Genetic Algorithm shows that travelled distance and traveled time were minimized when compared with existing results, the ability of Genetic Algorithm to diversify solution proved its effectiveness.

Keywords: Genetic Algorithm, Multi Depot Vehicle Routing Problem, Optimization, Optimization Techniques Evolutionary algorithm

Introduction

Multi Depot Vehicle Routing Problem (MDVRPs) is an extension of classical VRP with more than one depot, applicable to organizations that have several branches and each branch aimed at delivering goods or services to their customers simultaneously. The MDVRP can be seen as an issue of clustering since its production is a set of vehicle schedules clustered by the depot. This description entails an approach of clustering customers and scheduling the vehicles over each cluster. MDVRP is more challenging and complicated than the single-depot VRPs (Oliveira et.al., 2015). The Vehicle Routing Problem (VRPs) expands on the Travelling Salesperson Problem (TSP) with the addition of the bases, from which the traveling vehicles have to start and return to situations from the real-life problems have led to the numerous variations of this simple concept. Various approaches that use modern and recently introduced algorithms are described (Braekers et.al, 2016). The vehicle routing problem mostly includes various Real - world constraints. All those constraints have to be taken in to consideration when creating a feasible solution for real world usage; the most famous constraints are time windows. The time window represents the period when the customer can be served (Emir et.al, 2020). The figure 1 signifies the visual form of Multi Depot Vehicle Routing Problem:

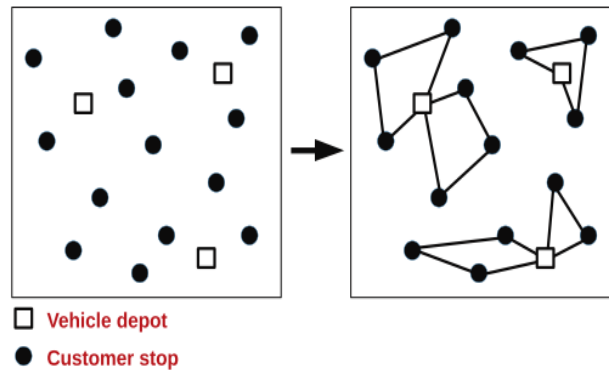


Figure 1 : Multi Depot Vehicle Routing Problem (Source: Karakati and Podgorelec, 2014).

MDVRPs simultaneously determine the routes for several vehicles from multiple depots to a set of customers and returns to same depot (Surekha and Sumathi, 2011). It is a well-known optimization problem with many real life applications in the areas of transportation, distribution and logistics (Contardo and Martinelli, 2014). To this extent research in optimization led to the development of different techniques for solving optimization problems such as TSP, MDVRP and other related optimization problems (Hashim et.al., 2016). Optimization process is usually guided by Optimization Search Techniques; these techniques are designed to provide the ‘best’ values of system design, values that will lead to the highest levels of system performance (Contardo and Martinelli, 2014). Figure 2 below depicts the search optimization techniques

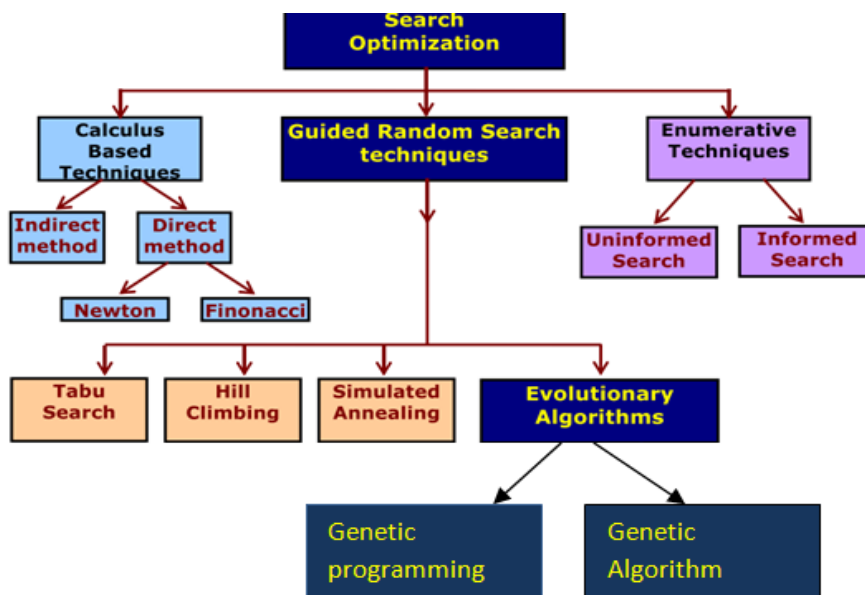


Figure 2: Taxonomy of Search Optimization techniques (Source: Chakraborty, 2010)

Since MDVRP is hard to solve with exact methods such as branch and bound, branch and cut algorithms, it is vital to apply evolutionary-based optimization techniques such as Genetic algorithms, Genetic Programming, Evolutionary Strategies (Surekha and Sumathi, 2011) to find the optimal solution to this optimization problem as it saves resources for a company, reduces expenses, shortens time needed to distribute services, and makes the company more competitive.

Evolutionary Algorithms (EA) is a metaheuristic inspired by natural selection and efficient strategies for solving optimization problems.(Oliveira et.al., 2015) Among the set of search and optimization

techniques, the development of EA has been very significant effort made in the last decade. EAs are a set of recent Meta heuristics used effectively in numerous applications with enormous complexity (Subramanian et.al., 2013). Evolutionary algorithms were the most commonly used strategy to solve the VRP, as surveyed by Karakati et.al., (2015). EA use a set named population to store data structures which represent solutions to the problem. Parallelism and its robust to dynamic changes, these among others makes it to be an outstanding method for solving large variety of combinatorial optimization problems.(Soonpracha et.al., 2015) Furthermore, (Mauro et.al., 2008) stated that EA involves mechanisms inspired by biological evolution such as reproduction, mutation, recombination, natural selection, and survival of the fittest. In this process, two main forces form the basis of evolutionary systems: Recombination and mutation create the necessary diversity and thereby facilitate novelty. At the same time, selection acts as a force increasing quality. Evolutionary Programming, Evolution Strategies, Genetic Algorithms, and Genetic Programming are sub-areas of EAs (Abraham, 2006). EAs usually undergo through the evolutionary process. The figure 3 below represents general scheme of evolutionary process were the subsequent described how co-evolutionary strategy was used in solving MDVRP.

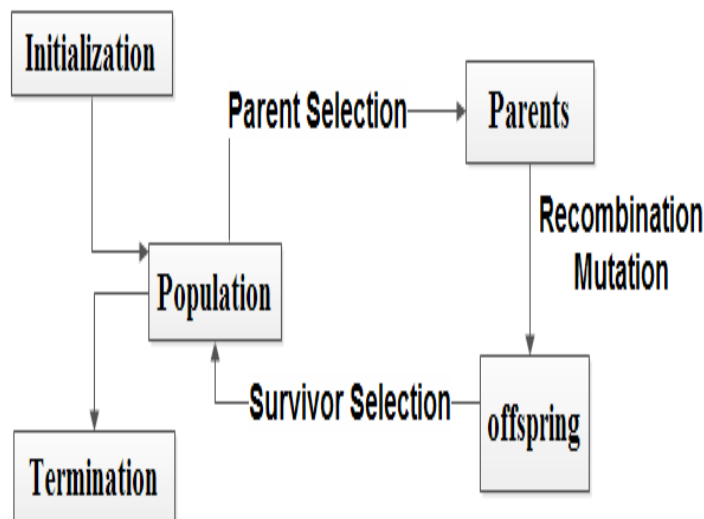


Figure 3: General Scheme of Evolutionary Process (Source: Eiben and Smith, 2015)

Cooperative Co-Evolutionary Algorithm (CoES) for Multi Depot Vehicle Routing Problem was Proposed by (Oliveira et.al., 2015), the problem is decomposed into smaller sub-problems and individuals from different populations are combined to create a complete solution to the original problem, sophisticated local search strategy was recommended. MDVRP was also solved and optimized using Genetic Algorithm (GA) by (Surekha and Sumathi, 2011), the customers are grouped based on distance to their nearest depots and then routed with Clarke and Wright saving method there the need for an efficient algorithm was stressed. Karakati et.al., (2015) in their work presented different genetic approaches, methods, and operators, commonly used in solving MDVRP were they required efficient operators for genetic crossover and mutation. The literature reviewed showed that most of the Algorithms designed were inadequate in using efficient assignment algorithm, efficient genetic operators, and sophisticated local search that will solve at minimal Travel Time and Travel Distance.

Perhaps, the above 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 used in Assigning (clustering) Customers to depots. This research solved MDVRP using the proposed Assignment Algorithm, which makes the problem to be solved at minimal travel distance and travel time and help vehicles to find routes such that all the customers are visited and scheduled efficiently. This will contribute in making good planning for the transportation fleet and make transportation material more utilized.

The main focus of our paper is to provide a design to improve route for clustering customers of MDVRP to the appropriate depot with the shortest travel distance and time. The article determines to overcome these challenges by proposing an efficient clustering (Assignment) algorithm to minimize travel distance and travel time of MDVRP.

2.0 Related Works

The vehicle routing problem (VRP) has been an open issue and the face of operational research and combinatorial optimization. As a variant of VRP, the multi-depot vehicle routing problem (MDVRP) has additionally attracted greater interest from scholars (YanJun et.al., 2020). Emir et.al., (2020) presented an adaptive data-driven innovative modular approach for solving the real-world vehicle routing problems (VRPs) in the field of logistics. The work consists of two essential units: (i) an innovative multi-step algorithm for successful and entirely feasible solving of the VRPs in logistics and (ii) an adaptive approach for adjusting and setting up parameters and constants of the proposed algorithm. Li et.al., (2019) used Ant Colony Optimization(ACO) to determine the solution of MDVRP variants, such as MDVRP with multiple objectives and MDVRP with time windows. Alinaghian and Shokouhi (2018) developed composite algorithm composed of an adaptive large neighborhood search and variable neighborhood search to solve this problem in which the load space of each vehicle has several sections, and each section is dedicated to a particular type of manufactured goods. YanJun et.al., (2020) stated that the multi-depot vehicle routing problem (MDVRP) additionally gained more consideration from scholars. The MDVRP problem is to assign customers with the demand to each depot under the condition that the supply of each depot is not be exceeded and arrange the order in which customers are visited by vehicles. The objective of the MDVRP is to minimize the total route length and the number of vehicles. At MDVRP, the number and location of the depot have been determined in advance. Each depot has certainly large enough to accommodate orders from customers. Every vehicle departs and returns to the depot, respectively. The l , The location and demand of each customer, are also known in advance, and every customer will be served precisely once (Fitriana et.al., 2019).

3.1 Mathematical Formulation of the Problem.

The mathematical formulation of MDVRP for this research was formulated from the below mathematical equations (1)-(8) presented by (Montoya-Torres et al., 2015), where In this formulation Constraints (2) and (3) guarantee that each customer is served by one and only one vehicle. Route continuity is represented by Constraints (4). The sets of constraints (5) and (6) are the vehicle capacity and total route cost constraints. Vehicle availability is verified by Constraints (7) and (8).

Minimize :

$$\sum_{i=1}^{N+M} \sum_{j=1}^{N+M} c_{ij} x_{ijk} \quad (1)$$

Subject to:

$$\sum_{i=1}^{N+M} \sum_{K=1}^K x_{ijk} = 1, j = 1, \dots, N \quad (2)$$

$$\sum_{j=1}^{N+M} \sum_{k=1}^K x_{ijk} = 1, i = 1, \dots, N \quad (3)$$

$$\sum_{i=1}^{N+M} x_{ihk} - \sum_{j=1}^{N+M} x_{hjk} = 0, \quad \begin{matrix} k = 1 \dots k \\ h = 1 \dots N + M \end{matrix} \quad (4)$$

$$\sum_{i=1}^{N+M} Q \sum_{j=1}^{N+M} x_{ijk} \leq P_k, k = 1, \dots, K \quad (5)$$

$$\sum_{i=1}^{N+M} \sum_{j=1}^{N+M} c_{ij} x_{ijk} \leq T_k, k = 1, \dots, K \quad (6)$$

$$\sum_{i=N+1}^{N+M} \sum_{j=1}^N x_{ijk} < 1, k = 1 \dots K \quad (7)$$

$$\sum_{j=N+1}^{N+M} \sum_{i=1}^N x_{ijk} < 1, k = 1 \dots K \quad (8)$$

Let $G = (V, A)$ be a directed graph, where V is the set of nodes, and A is the set of arcs, the nodes are divided into two subsets: the multiple incapacitated depots, Vehicle Depots $(VD) = \{1 \dots M\}$, and the customers to be served, Vehicle Customers $(VC) = \{M+1, \dots, M+C\}$, $V = M \cup C$ is the vertex or node set. A travelling cost, $c_{ij} > 0$, is defined for each arc between each pair of vertices (i, j) . The demand of each customer is d_i (there is no demand at the depot nodes). There is also a fleet of K vehicles, each with capacity Q . The service time at each customer i is t while the maximum route interval time is set to Execution Time. In this work, however, the cost is the same as distance units, and the number of iteration is the amount of looping taken by the program to execute the algorithm.

1. Every vehicle route starts and ends at the same depot
2. Every customer must be visited on precisely one vehicle.
3. The whole demand of the customers on every route does not surpass the capacity of the vehicles, that is, Q .
4. The overall cost of the distribution is minimized.

3.2 Efficient Assignment Algorithm

The process starts with the set of customers V_C , the set of vehicle depots V_D , as well as the set of arcs A . In Line 4 the closest customer m_i to depot V_D is chosen according to rule 1 and inserted in the assignment cluster Am_i of depot V_D in Line 5. The algorithm checked to see if there are still customers to be allocated to the depot. If there are, the closest neighbor to last assigned customer, is defined as customer Am_i (Line 9) and the closest customer to the last assign customers j , identified as m_j , is selected according to rule 2, The customers are compared in Line 10. If the two customers are different ($m_i \neq m_j$), customer i is also inserted in the allocation group Am_i of customer m_j (Line 11). After processing all customers, the assignment groups are returned (Line 11). The complexity of the whole algorithm is (in the worst case) $O(dc+c^2)$, c is the amount of customers, and d is the amount of depots. Figure 4 shows the detail of the algorithm.

```
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(Ami, i);
Step8: if (mi ≠ mi) then // different customers
Step9: insert(Ami, Ami);
Step10: End If
Step11: End while
Step12: End for
Step13: End for
Step14: Return (A1.....Ami);
Step15: END.
```

Figure 4: Proposed clustering algorithm

3.3 GA - MDVRP

In this research work, Genetic Algorithm was used to solve MDVRP, we named the solution (results obtained) of MDVRP using GA as GA-MDVRP. Random population acknowledged as the chromosome (genes) were generated and assessed using fitness function which allows the distribution 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 reliability of a solution with respect to the present population is determined. The population was partitioned using an Island approach (Island Evolution) to permit parallel computing to attain its count; the population was broken down into category of 16 individual bits, the breakdown approach employed, clustered closest customers to every depot and assign the closest customer to the last assign customer and allows solving each sub problem in parallel.

3.4. GA- MDVRP Implementation

MDVRP was implemented using MATLAB and evaluated on the 33 MDVRP benchmark instances extracted from (Cordeau & Gendreau, 2012; Oliveira et'al., 2015; Vidal et'al., 2016). These benchmarks were grouped into S1 (P01-P23) and S2 (P24-P33). 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 simulated 5 times using the parameters M for number of depots 1.....M, N for Number of customers 1....N, and Q for vehicle capacity (M,N,Q) specified in Table1 below to extract the mean values for the minimum travel distance and travel time of the experiment. Figure 5 represent an implemented.

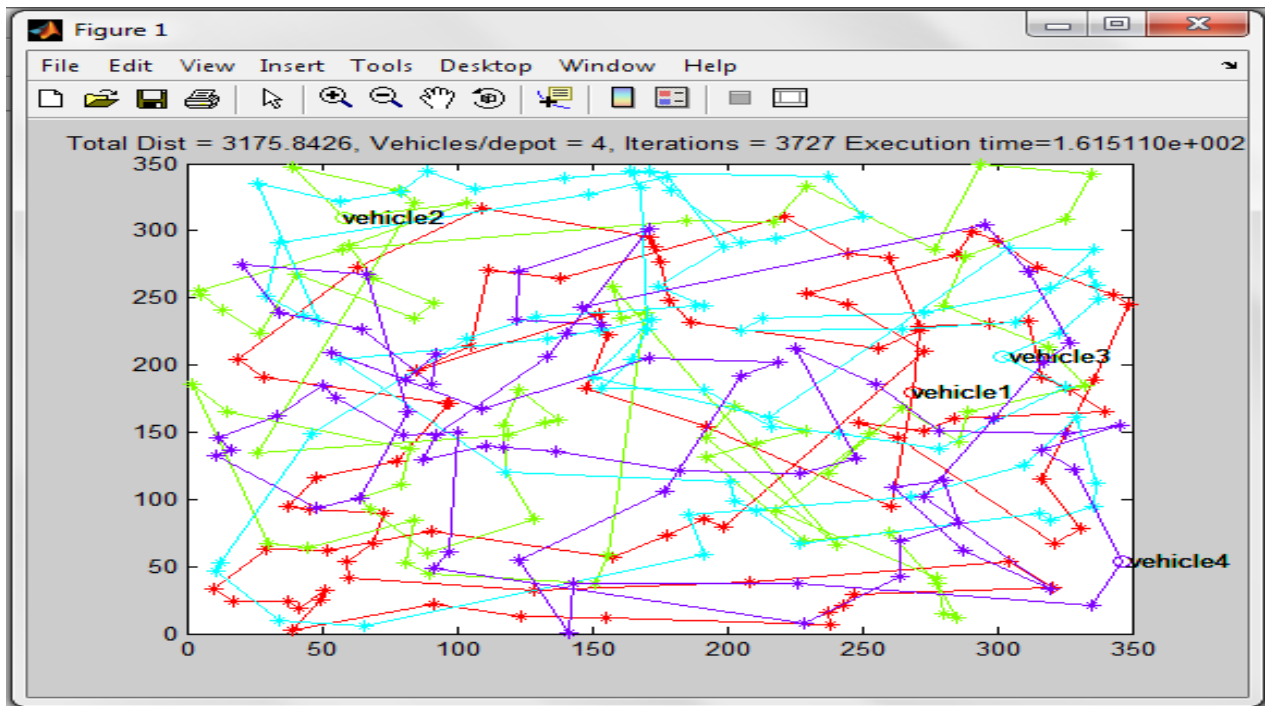


Figure 5: Implemented MDVRP (Source: implemented GA - MDVRP)

3.5 Performance Analysis for the Proposed Ga-Mdvrp

The Table 1 below indicated the results obtained from the experiment conducted for S1 and S2 Benchmark instances, the mean values of travel distance as well as the travel time of all the benchmark instances were recorded as shown on the Table 1 below.

Table 1: Proposed GA-MDVRP result for S1 Benchmark Instances

Proposed GA- MDVRP					
Instances				Mean Values	
Instance	M	N	Q	Time(s)	Cost(Distance)
P01	4	50	80	0.80	473.96
P02	2	50	160	0.20	453.93
P03	3	75	140	1.00	598.05
P04	8	100	100	169.91	973.54
P05	5	100	200	18.20	749.73
P06	6	100	100	67.43	768.35
P07	4	100	100	21.56	898.89
P08	14	249	500	700.26	3629.52
P09	12	249	500	503.63	3312.31
P10	8	249	500	702.96	3211.32
P11	6	249	500	372.91	3495.48
P12	5	80	60	0.76	1244.57
P13	5	80	60	0.00	1280.61
P14	5	80	60	0.00	1296.08
P15	5	160	60	91.92	2234.00
P16	5	160	60	6.50	2335.62



P17	5	160	60	13.62	2414.25
P18	5	240	60	410.20	3664.45
P19	5	240	60	67.70	3780.07
P20	5	240	60	186.37	4035.93
P21	5	360	60	512.78	5561.50
P22	5	360	60	204.05	5701.98
P23	5	360	60	511.36	5998.69
P24	1	48	200	0.00	769.16
P25	2	96	195	529.70	1033.71
P26	3	144	190	100.98	1562.89
P27	4	192	185	433.42	1944.76
P28	5	240	180	223.38	2153.20
P29	6	288	175	529.19	2538.26
P30	1	72	200	0.45	959.646
P31	2	144	190	205.39	1598.65
P32	3	216	180	447.54	2050.66
P33	4	288	170	306.63	2588.62
				Total	75312.39

3.6 Comparison with Existing result

To determine the extent to which the parameters were improved, the mean values of the results obtained for the table1 were compared with the most recent work done in the area to validate the proposed algorithm.

Table 2 : Comparison Proposed of GA-MDVRP result and CoES result for S1

Instance	Proposed GA – MDVRP					CoES	
	M	N	Q	Mean Values		Mean Values	
				Time(s)	Cost	Time(s)	Cost
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

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
Total				7340.8	75312.39	8635.1	80831.84

Figure 5 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 CoES. This shows the effectiveness of GA in solving MDVRP since it improved the solution quality for a number of instances.

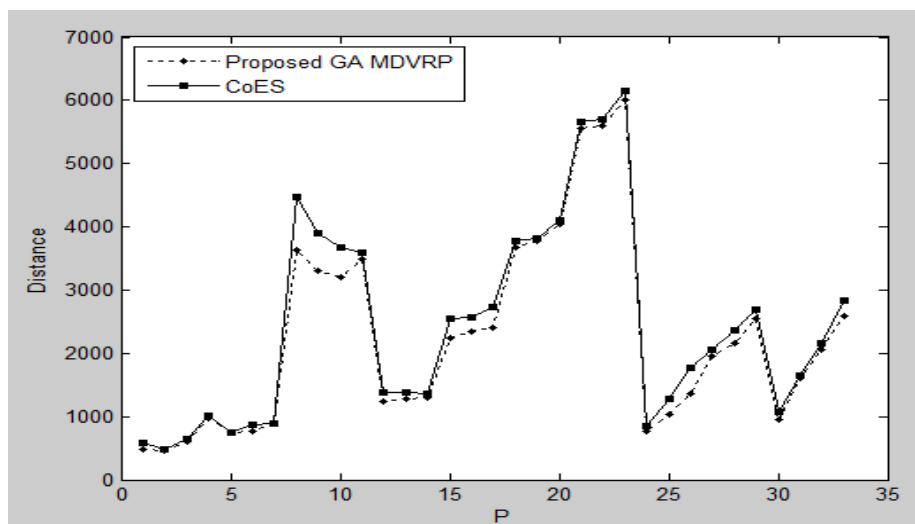


Figure 6: Travel Distance of GA-MDVRP compared with COES for all the benchmark instances (S1 & S2)

Figure 6 indicated the benchmark instances S1(P01 to P23) against Travel Distance for GA-MDVRP and CoES, this shows the travel distance was drastically minimized in contrast with the Cooperative co-Evolutionary Strategy(CoES).

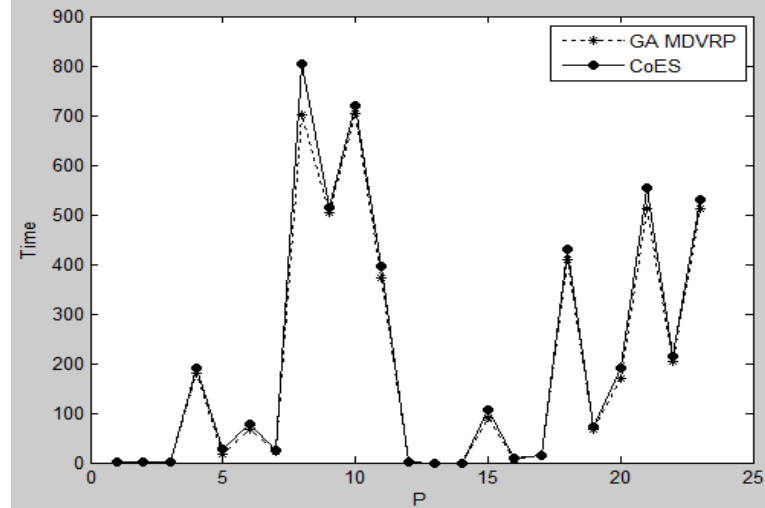


Figure 7: Travel Time of GA-MDVRP compared with CoES for S1.

4. Conclusion

Multi Depot Vehicle Routing Problem requires frequent research because of the increasing number of organization aimed at distributing goods and services to the customers, new approaches to attempt large scale real time problem and more rational constraint need to be researched in future, in order to ensure a reliable reduction of travel cost, travel distance, and travel time. The contribution of this research work revolve around providing a system for an organization which have several branches a means to make good planning for the transportation of goods or services to their customers and make transportation material more utilized which will help minimized the price of goods.

It was observed from the results of simulation obtained, the CoES total travelled distance was 80831.84 km and travelled time of 8635.1s; while total travelled distance for the proposed Genetic Clustering Algorithm was 75312.39 km and travelled time of 7340.8s. the result obtained shows the performance of GA was exceptional and the computational time proved that optimization using GA is much faster and the travelled time minimized proved GA does well in finding smaller gene subsets and better accuracies for solving of Multi-Depot Vehicle Routing Problem.

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