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Solution to a Multi Depot Vehicle Routing Problem Using K-means Algorithm, Clarke and Wright Algorithm and Ant Colony Optimization

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Abstract

Vehicle routing problem (VRP) is a very important combinatorial optimisation problem. The subject is simple to explain however tough to attain an optimum solution because of high processing quality. Single-Depot Vehicle routing problem aren't appropriate for sensible things. Vehicle Routing problem with more than one depot are called Multi-Depot VRPS. The Multi-Depot Vehicle Routing Problem (MDVRP) is an extension of classical VRP, may be an NP-hard problem and at the same time determinative for the routes of many vehicles from multiple depots to a collection of customers and come back to the respective depot. The objective of the MDVRP is to serve all customers while minimizing the total travel distance under the constraint that the total demands of served customers cannot exceed the capacity of the vehicle for each route. MDVRP constitutes both location allocation of new depot and also routing of Vehicles. The Location Allocation of new Depots is determined using K-means Clustering algorithm and Routing is done using Clarke & Wright algorithm. The solutions evaluated from the above Clarke & Wright algorithm are then analyzed and compared with Meta heuristics like Ant Colony Optimization.

Keywords: Multi-Depot Vehicle Routing, k-means algorithm, clustering, Clarke & Wright algorithm, Ant colony optimization.

INTRODUCTION

In the fast-developing logistics and supply chain management fields, one of the key problems in the decision making system is that how to arrange a proper supply chain for a lot of customers and suppliers and produce a detailed supply schedule under a set of constraints. Solutions to the multi-depot vehicle routing problem (MDVRP) help in solving this problem in case of transportation applications. Given the locations of depots and customers, the MDVRP requires the assignment of customers to depots and the vehicle routing for visiting these customers. Each vehicle originates from one depot, serves the customers assigned to that depot, and returns to the same depot. The objective of the MDVRP is to serve all customers while minimizing the total travel distance under the constraint that the total demands of served customers cannot exceed the capacity of the vehicle for each route. There is an important assumption in the MDVRP namely that unlimited number of vehicles are located in each depot. However, in fact, it is obvious that this assumption is not reasonable in most cases in the real business applications since no company has unlimited number of vehicles. Considering the constraint of the limited number of vehicles, we propose a new widely applicable variant of the MDVRP. The MDVRP is solved separately by "Assignment first, Route second". In this paper the we used two algorithms, K-means algorithm for the assignment of demand points to the nearest depot by forming clusters and Clarke & Wright method for routing of vehicles .There are three levels in solving MDVRP, i.e., assigning customers to depots, assigning customers to vehicles within one depot and routing for single vehicle.

The standard formulation of MDVRP can be enhanced on introducing a capacity constraint. Each customer at a particular node in the city will have a specific demand and also the maximum capacity of each vehicle that it can fulfill will be taken into consideration. If any one of the customer on the route has maximum load than the threshold limit then the vehicle should return to the warehouse or depot rather continuing to the customer. In the similar way another constraint can be set by limiting the length of the individual route. The most challenging factor in the field of supply chain management and logistics industry is the way of optimizing the product delivery from suppliers to customers without violating the constraints. Such problems are known as Vehicle Routing Problems (VRP), in which the vehicles leave the depot, serve's their assigned customers and finally return to the depot after the demands are completely satisfied. Each customer or a node has their own demand. If the problem is related with only one depot then the VRP is named Single-depot VRP. In case the problem is dealt with more than 1 depot then the VRP's are known as multi-depot VRPs (MDVRP). Single-depot VRPs despite attracting most of the researchers they are practically not efficient in most of the cases when large area of interest is taken into consideration, here it lies the need in introducing MDVRP. In MDVRP, since there are a large number of depots, it becomes a very difficult task for an operation manager to assign the vehicles to their relevant depots without violating the capacity constraints. Hence clustering is performed to group the customers based on distance from the warehouse or depot, prior to the routing and scheduling phases. As these Vehicle routing problems are NP-hard, it is impossible to obtain optimal solution using exact methods and hence heuristic algorithms have been developed to solve the MDVRPs at a faster rate for providing efficient solutions. The main objective of the problem is concentrated on minimizing the total cost of combined routes for a fleet Of vehicles. Since cost is associated with distance, in general, the goal is to minimize the distance travelled by applying the bio-inspired Ant Colony Optimization. Rest of the paper is organized as follows Literature review in section II, Methodology and Methods in Section III, Data Collection in section IV, Results Evaluation and Analysis in section V, Discussion and Conclusion in section VI followed by references at the end.

LITERATURE REVIEW

In the literature, there are a number of published work dealing with the traditional MDVRP. The first heuristics were proposed by Tillman. Wren and Holliday described a heuristic consisting of two parts: constructing an initial solution, followed by a method of saving in each depot and refinements. Gillett and Johnson presented a clustering procedure and a sweep heuristic in each depot.

Golden *et al.* presented two heuristics for solving the MDVRP. The first is an adaptation of savings methods; the second is designed for larger-scale problems to save the on computing time. The second heuristic is a two-stage “assignment first and route Second” method. The literature on exact approaches for the MDVRP is sparse. In fact, most authors have focused on the development of heuristic methods to find good quality solutions quickly.

The most recent exact method reporting results on the MDVRP is that of Baldacci and Mingozzi. The method is based on the additive bounding procedure of Christofides et al applied to several different relaxations of the problem. Ultimately, the set-partitioning formulation of the MDVRP is solved by means of column generation strengthened with the so-called strong capacity constraints and clique inequalities. They do not consider the inclusion of the route length constraint and so experiments are conducted only on those instances without such requirement. A problem closely related to the MDVRP is the periodic VRP (PVRP), in which the complete planning horizon is subdivided in periods, and vehicle routes cannot be longer than the length of one period. The MDVRP can be formulated as a PVRP by realizing that different depots can be modeled as multiple periods in the context of a PVRP. Therefore, any algorithm that solves the PVRP can also solve the MDVRP.

Baldacci et al. proposed an exact algorithm for the PVRP that generalizes their former method for the MDVRP but, as remarked by the authors, does not improve upon their

Previous results.

Amberg et al (2000) in his paper mainly focused on Capacitated arc routing problem which has Multiple number of centres the main aim is to find out the optimum route starting from the initial depot or centre by satisfying various constraints involved and thereby reducing the travelling cost. Here he used a heuristic algorithm called Capacitated Minimum Spanning tree. Additionally in this paper he also mentioned the possibilities to introduce additional and side constraints into the objective function. After evaluating the results with the real world problems he compared them with Tabu Search, Simulated Annealing and various other Meta Heuristic algorithms.

Mohibul Islam, Sajal Ghosh (2015) in his paper also dealt with the case of capacitated vehicle routing problem. In this basically a real time data of a Coca-Cola distribution company in Bangladesh are taken at various nodes and analyzed and evaluated using various heuristic algorithms like Clarke and wright algorithm, Holmes and Parker algorithm and Fisher and Jaikukumar algorithm and compared the results among them and concluded that Clarke and wright algorithm proved to be more effective for his work and also mentioned that these heuristic algorithms might provide better results for small instances and might be ineffective when the problem becomes complex.

Watanabe and Sakakibara (2007) in the present paper mainly focused on the ways of translating single objective optimization problem into multi objective optimization problem and by using various evolutionary algorithms he stated that the results of multi objective optimization are far better than single objective optimization. Further he also described the differences of dividing the problem into subways and compared them with the traditional methods of solving the problems.

METHODOLOGY AND METHODS

In this paper the we used three algorithms, K-means algorithm for the assignment of demand points to the nearest depot by forming clusters and Clarke & Wright method for routing of vehicles and these routes are evaluated with a Meta heuristic Algorithm i.e. Ant Colony Optimization.

A. K Means Algorithm:

It is a Centroid-based clustering, central vector represents the number of clusters which is not necessary to be a member of the data set. When we fix number of clusters to *k*, a formal definition of an optimization problem is given by *k*-means clustering: finding the *k* cluster centers and assign the objects to their nearest cluster center in the following manner to the cluster which gets the minimum squared distance.

Algorithmic steps for k-means clustering:

1. Initially based on the area or city considered we will decide with the number of clusters or depots to be formed.
2. Let us consider there are ‘n’ nodes in a city with their co-ordinates $\{ x_1,x_2,x_3\ldots.. x_n , y_1,y_2,y_3,\ldots\ldots y_n \}$, and allot the points initially as cluster 1 , cluster 2 etc.. Based on the required number of clusters as decided earlier.

3. Now calculate the Euclidean distances from the selected clusters "k" to the remaining nodes in the city and allot the individual node to the cluster which has a minimum Euclidean distance from the nodes.
4. After allotting the node to the respective cluster, update the new centroid of the respective cluster by calculating the mean of those two points.
5. In this way by calculating the Euclidean distances nodes are allotted to different clusters and also by updating the mean value new centroids are formed.
6. In this way clustering of the nodes is done.

B. Clarke and Wright Savings Algorithm:

Clarke & Wright algorithm an algorithm used to provide solutions to vehicle routing problems was introduced in the year 1964, this algorithm mainly uses the concept of Savings to determine the solution. A distance matrix is prepared which provides us the details of the distance between various nodes present in the city and also the distance between the nodes and the warehouse also. The costs can be used in place of distance, if the transportation costs between every pair of nodes is available with us.

The distance d_{ij} on a grid between a points i with a coordinates (x_i,y_i) and a point j with a coordinates (x_j, y_j) is evaluated as:

$$\mathbf{D_{ij}= \sqrt{((x_i-x_j))^2+ (y_i-y_j)^2}}$$

Algorithmic steps involved:

1. Initial solution: Each individual vehicle serves the available 'n' nodes.
2. Calculate the *savings* for joining the cycles using edge [i,j], using the formula :$\mathbf{S_{ij} = D_{0i} + D_{0j} - D_{ij}}$.
3. $\mathbf{nC_2}$ number of savings will be obtained on calculating using the above formula.
4. Sort the savings in descending order.
5. Consider the highest saving and assign it to the vehicle by satisfying the capacity constraint.
6. Now move on the next highest saving and assign it to the same vehicle if it satisfies the capacity constraint of the vehicle.
7. If it violates the capacity constraints move on to the next highest savings which satisfies the capacity constraints.
8. In this way all the nodes are assigned to the vehicles without violating the capacity constraints.

C. Ant Colony Optimization:

1. Ant Colony Optimization a Meta heuristic algorithm was proposed by Gambardella Dorigo in the year 1997.
2. This is a Probabilistic technique in which search for optimal path in the graph based on the behaviour of ants seeking path between their colony and source of food.
3. Each ant moves at random and navigate from the nest to food source, shortest path is discovered via pheromone trails, Pheromone is deposited on the path, and more pheromone on the path increases the probability of path being followed.
4. An ant will move from node i to j with a probability of

$$p_{ij}^k = \frac{\tau_{ij}^\alpha \cdot \eta_{ij}^\beta}{\sum_{l \in N_i^k} \tau_{il}^\alpha \cdot \eta_{il}^\beta}$$

Where $\boldsymbol{\eta_{ij} = 1 / d_{ij}}$, $\boldsymbol{\eta_{ij}}$ is the visibility of city j from i. τ_{ij}^α is the intensity of pheromone trail between i and j

α is the parameter to regulate the influence of pheromone, usually it will be between 0 and 1.

β is the parameter to regulate the influence of visibility , usually between 0 and 1.

5. These parameters are the random numbers [0,1].
6. Initially by using this formula the probability of all the possible nodes are calculated by satisfying the demand and the capacity constraints.
7. Then the ant tends to choose the path with highest probability.
8. This process is carried out until the capacity of the ant is fulfilled and next iteration starts from the starting node for another ant.
9. Same process is repeated for the next upcoming ants until all the demands at different nodes are fulfilled.
10. Stop the process after all the nodes get allocated to required number ants, which provides us with an optimal route.

DATA COLLECTION

- The Data such as Demand, distances of demand points (13 nodes) from an existing warehouse (Logistics Company). With the help of the map the distance of demand points from the ware house has been calculated and then formed the distance matrix. The Circle in origin represents warehouse location
- There is a capacity constraint for this data, i.e, a route or a delivery person cannot exceed ***75*** deliveries (demand) per day.

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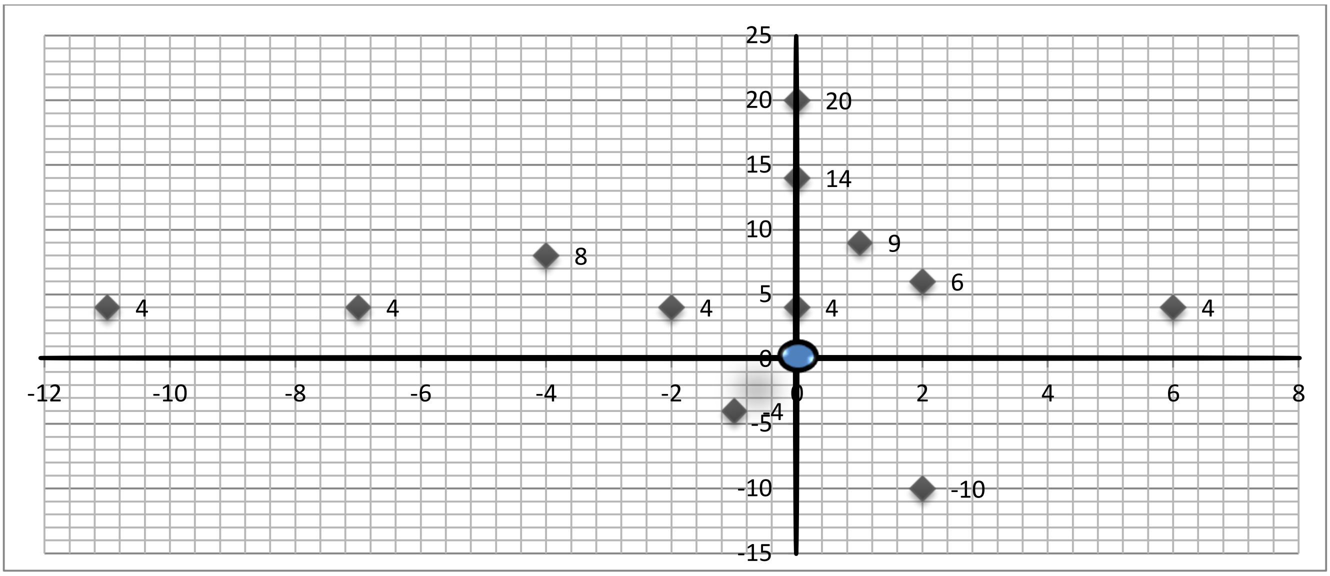

Figure 1. Distance Map

Table 1. Distance matrix

	0	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**
0	**-**	10	14	6	10	12	12	20	11	8	15	4	5	10
1	10	-	16	8	10	14	20	22	13	6	17	6	16	16
2	14	16	-	12	6	10	26	6	17	10	21	10	19	10
3	6	8	12	-	8	6	14	18	5	6	9	2	9	5
4	10	10	6	8	-	6	22	12	13	5	17	6	4	6
5	12	14	10	6	6	-	20	16	7	8	11	8	15	2
6	12	20	26	14	22	20	-	32	23	18	27	16	9	20
7	20	22	6	18	12	16	32	-	23	16	27	16	25	16
8	11	13	17	5	13	7	23	23	-	11	4	7	16	7
9	8	6	10	6	5	8	18	16	11	-	15	4	13	6
10	15	17	21	9	17	11	27	27	4	15	-	11	20	11
11	4	6	10	2	6	8	16	16	7	4	11	-	9	6
12	5	16	19	9	4	15	9	25	16	13	20	9	-	13
13	10	16	10	5	6	2	20	16	7	6	11	6	13	-

Table 2. Demand Matrix

Node	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**	**11**	**12**	**13**
D_i	30	40	45	30	20	40	35	30	35	30	28	25	42

Assumptions:

1. The problem is static; all orders are known a priority.
2. Transportation cost is directly proportional to the distance travelled.
3. Backhauls are not permitted.
4. All orders are consolidated to full truckloads and don't exceed the vehicle capacity.
5. Each vehicle has Time windows for each order have to be adhered strictly.
6. To start and return to the collection center after each tour.

- So as of now based on the demand and capacity constraints, without using any algorithm we require 7 vehicles in order to satisfy the demands at various nodes.

- Hence total distance travelled is given by (Distance from depot to every node + Distance from every node to depot), each vehicle covers 2 nodes and distance travelled will be **274 KM's** per day.
- When we introduce a capacity constraint to each vehicle, this assignment would become complex and hence there it lies the necessity of an Algorithm. As mentioned earlier the algorithm that is used for routing of Vehicles is Clarke & Wright Algorithm.

RESULT EVALUATION AND ANALYSIS

Single Depot Vehicle Routing Problem:

In the case of Single Depot Vehicle Routing problem the warehouse is located at (0, 0) and all the vehicles starts from the warehouse and returns to the warehouse. Hence there is no requirement of clustering here. Hence we can directly apply Clarke and Wright Savings Method here and the results obtained are given in the table.

Table 3. Comparison Table of SDVRP

	Route	**Distance**	**Load**	**Cumulative distance (km)**
Single depot without Clarke & Wright method (Assigned Randomly)	0-1-2-0	40	70	238
	0-3-4-0	24	75	
	0-5-6-0	44	60	
	0-7-8-0	54	65	
	0-9-10-0	38	65	
	0-11-12-0	18	53	
	0-13-0	20	42	
Single Depot with Clarke & Wright	0-2-7-0(**V_1**)	40	75	194
	0-8-10-0(**V_2**)	30	60	
	0-5-13-0(**V_3**)	24	62	
	0-4-1-0(**V_4**)	30	60	
	0-9-12-0(**V_5**)	26	60	
	0-3-0(**V_6**)	12	45	
	0-6-11-0(**V_7**)	32	68	

Hence here we can notice that when we assigned vehicles randomly by satisfying the capacity constrained , vehicles covered a distance of 238 Km's per day and when we introduced Clarke and Wright Algorithm the distance travelled by the same number of vehicles got reduced to 194 Km's per day.

Multi Depot Vehicle Routing Problem:

In the case of Multi Depot Vehicle Routing Problem, when a logistic company has to serve a large area or a large city it becomes very difficult to manage the delivery to all the nodes in the city and the transportation costs increases, and here it lies the importance in introducing the "Multi Depot Vehicle Routing Problem". The main difference between Single depot and Multi Depot is there will be multiple warehouses in the city for Multi Depot Vehicle Routing Problem. Now the Question arise is where theses Warehouses Should be Located? The answer to this will be given by Introducing "K Means Clustering" Algorithm. By using this algorithm we divide the depots and evaluate the results and conclude when we get an optimum result.

2-Depot Vehicle Routing Problem:

By using the k-means algorithm, the two Centroid points obtained are A = (-2.5, 3.5), B=(-1, 15)

Being A,B as centroids, two clusters are formed.

- Nodes 1,3,6,8,9,10,11,12,13 are assigned to warehouse A- **Cluster -1**
- Nodes 2,4,5,7 are assigned to warehouse B- **Cluster-2**

Now here we will apply Clarke and Wright Algorithm for both the clusters.

Cluster 1:

On applying Clarke & Wright to cluster 1

- Total distance travelled in Cluster 1 is **93 Km's**.
- Total number of vehicles used are **"5"**

Table 4. Distance matrix of Cluster-I

	A	**1**	**3**	**6**	**8**	**9**	**10**	**11**	**12**	**13**
A	-	9	1	17	6	7	10	3	10	4
1	9	-	8	20	13	6	17	6	16	16
3	1	8	-	14	5	6	9	2	9	5
6	17	20	14	-	23	18	27	16	9	20
8	6	13	5	23	-	11	4	7	16	7
9	7	6	6	18	11	-	15	4	13	6
10	10	17	9	27	4	15	-	11	20	11
11	3	6	2	16	7	4	11	-	9	6
12	10	16	9	9	16	13	20	9	-	13
13	4	16	5	20	7	6	11	6	13	-

Cluster 2:

On applying Clarke & Wright to cluster 2

- Total distance travelled in Cluster 2 is **39 Km's**.
- Total number of vehicles used are **"2"**

Table 5. Distance matrix of Cluster-II

	B	**2**	**4**	**5**	**7**
B	-	2	8	11	6
2	2	-	6	10	6
4	8	6	-	6	12
5	11	10	6	-	16
7	6	6	12	16	-

- Hence Total distance travelled will be = Distance travelled in Cluster 1 + Distance travelled in Cluster 2

  = 93 + 39

  = 132 Km's.

- Total Number of Vehicles Used = 7

3- Depot Vehicle Routing Algorithm:

Here 3 centroid points obtained using k-means algorithm are A= (2,-4), B (0.5, 16), C (-3, 6)

- Nodes 1,6,12 are assigned to- **Cluster 1**
- Nodes 2,4,7 are assigned to - **Cluster 2**
- Nodes 3,5,8,9,10,11,13 are assigned to – **Cluster 3**

Cluster 1:

On applying Clarke & Wright to cluster 1

Table 6. Distance matrix of Cluster-I

	A	**1**	**6**	**12**
A	-	12	6	3
1	12	-	20	16
6	6	20	-	9
12	3	16	9	-

Total distance travelled in Cluster 1 is **42 Km's**.

Number of vehicles used are **"2"**

Cluster 2:

Applying Clarke & Wright to Cluster 2

Table 7. Distance matrix of Cluster-II

	B	**2**	**4**	**7**
B	-	2	8	6
2	2	-	6	6
4	8	6	-	12
7	6	6	12	-

Distance travelled in Cluster 2 is **28 Km's.**

Number of Vehicles used are **"2".**

Cluster 3:

On applying Clarke & Wright to cluster 3

- Total distance travelled in Cluster 1 is **48 Km's**.
- The number of vehicles used are **"4"**

Table 8. Distance matrix of Cluster-III

	C	**3**	**5**	**8**	**9**	**10**	**11**	**13**
C	-	3	3	6	5	10	5	1
3	3	-	6	5	6	9	2	5
5	3	6	-	7	8	11	8	2
8	6	5	7	-	11	4	7	7
9	5	6	8	11	-	15	4	6
10	10	9	11	4	15	-	11	11
11	5	2	8	7	4	11	-	6
13	1	5	2	7	6	11	6	-

- Hence Total distance travelled will be = Distance travelled in Cluster 1 + Distance travelled in Cluster 2+

  Distance travelled in Cluster 3

  = 42+28+48

  = **118 Kms**.

- Total Number of Vehicles Used = 2+2+4=**8**
-

Table 9. Results obtained for different Combinations

Combination	**Route**	**Distance**	**LOAD**	**Cumulative Distance(km)**	**No. of vehicles used**
Single depot without Clarke & Wright method	0-1-2-0 0-3-4-0 0-5-6-0	40 24 44	70 75 60	238	7

Combination	Route		Distance	LOAD	Cumulative Distance(km)	No. of vehicles used
	0-7-8-0		54	65		
	0-9-10-0		38	65		
	0-11-12-0		18	53		
	0-13-0		20	42		
Single Depot with Clarke & Wright	0-2-7-0(V_1)		40	75	194	7
	0-8-10-0(V_2)		30	60		
	0-5-13-0(V_3)		24	62		
	0-4-1-0(V_4)		30	60		
	0-9-12-0(V_5)		26	60		
	0-3-0(V_6)		12	45		
	0-6-11-0(V_7)		32	68		
2-Depot with C&W	Depot-A	A-6-12-A(V_1)	36	65	93	***7***
		A-8-10-A(V_2)	20	60		
		A-1-9-A(V_3)	22	65		
		A-11-13-A(V_4)	13	70		
		A-3-A(V_5)	2	45		
	Depot-B	B-4-5-B(V_6)	25	50	39	
		B-2-7-B(V_7)	14	80		
Total Distance	***93+39=132***					
3- Depot with C&W	Depot-A	A-1-6-A(V_1)	18	65	42	8
		A-1-A(V_2)	24	30		
	Depot-B	B-2-4-B(V_3)	16	70	28	
		B-7-B(V_4)	12	35		
	Depot-C	C-8-10-C(V_5)	20	60	48	
		C-3-11-C(V_6)	10	73		
		C-9-5-C(V_7)	16	55		
		C-13-C(V_8)	2	42		
Total Distance					42+28+48=118	

Application of ACO to 2- Depot Problem:

According to ACO, with the help of probability equation, the node with highest probability (from depot) is assigned first, then the node with highest probability from previously assigned node respectively. The obtained Routes & Probability values of 2 Depot problem using ACO are tabulated and then compared with that of values obtained using Clarke & Wright method.

ACO for Cluster – 1:

Table 10. Probability table for Cluster 1

Iteration number	Available nodes with their Probability	Selected node based on highest prob.	Demand	Vehicle Allotted	Distance travelled (km)	Capacity remaining
1 (From Depot A)	2(0.449) 4(0.165) 5(0.126) 7(0.207)	2	40	V_1 (A-2-?)	2	35
1^1 (From Node 2)	4(0.376) 5(0.247) 7(0.376)	7	35	V_1 (A-2-7-A)	2+6+6=14	0 (No further allotment)
2 (From Depot A)	4(0.165) 5(0.126)	4	30	V_2 (A-4-?)	8	45
2^1 (From Node 4)	5 (remained)	5	20	V_2 (A-4-5-A)	8+6+11=25	25(no further allotment)

- Distance travelled using Cluster – 1 = 14+25 = **39 kms**
- No. of Vehicles used = **"2".**

ACO for Cluster -2:

Table 11. Probability table for Cluster 2

Iteration number	Available nodes with their Probability	Selected node based on highest prob.	Demand	Vehicle Allotted	Distance travelled	Capacity remaining
1 (from Depot B)	1(0.0657) 3(0.358) 6(0.035) 8(0.083) 9(0.073) 10(0.054) 11(0.143) 12(0.054) 13(0.115)	3	45	V_1 (B-3-?)	1	30

1^1 (from node 3)	8(0.267) 11(0.55) 12(0.177)	11	28	V_1 (B-3-11-B)	1+2+3= 6	2 (no further allotment)
2 (from Depot B)	1(0.0657) 6(0.035) 8(0.083) 9(0.073) 10(0.054) 12(0.054) 13(0.115)	13	42	V_2 (B-13-?)	4	33
2^1 (from node 13)	1(0.247) 8(0.324) 10(0.213) 12(0.213)	8	30	V_2 (B-13-8-B)	4+7+6= 17	3 (no further allotment)
3 (from Depot B)	1(0.0657) 6(0.035) 9(0.073) 10(0.054) 12(0.054)	9	35	V_3 (B-9-?)	7	40
3^1 (from node 9)	1(0.419) 6(0.157) 10(0.201) 12(0.221)	1	30	V_3 (B-9-1-B)	7+6+9= 22	10 (no further allotment)
4 (from Depot B)	6(0.035) 10(0.054) 12(0.054)	10	30	V_4 (B-10-?)	10	45
4^1 (from node 10)	6(0.443) 12(0.556)	12	25	V_4 (B-10-12-B)	10+20+10= 40	20 (no further allotment)
5	6 (remained)	6	40	V_5 (B-6-B)	17+17= 34	35 (no further allotment)

- Distance travelled in Cluster 2 = 6+17+22+40+34 =**119 kms**
- Number of Vehicles used are **“5”**

- Total Distance travelled using ACO for 2- Depot problem = Distance from Cluster 1 + Distance from Cluster 2
  = 39+119
  = 158 Kms
- Total number of vehicles used are **“7”**

Comparison of Best solution of Heuristic Algorithm with Metaheuristic Algorithm:

Table 12. Heuristic vs. Metaheuristic Algorithm

<table>
<tr><th>ALGORITHM</th><th>DEPOT</th><th>ROUTE</th><th>DISTANCE</th><th>LOAD</th><th>CUMULATIVE DISTANCE(KM)</th></tr>
<tr><td rowspan="7">2 Depot using
ACO</td><td rowspan="2">Depot-A</td><td>A-2-4-A(V_1)</td><td>16</td><td>70</td><td rowspan="2">49</td></tr>
<tr><td>A-7-5-A(V_2)</td><td>25</td><td>55</td></tr>
<tr><td rowspan="5">Depot-B</td><td>B-3-11-B(V_3)</td><td>6</td><td>73</td><td rowspan="5">119</td></tr>
<tr><td>B-13-8-B(V_4)</td><td>17</td><td>72</td></tr>
<tr><td>B-9-1-B(V_5)</td><td>22</td><td>65</td></tr>
<tr><td>B-10-12-B(V_6)</td><td>40</td><td>55</td></tr>
<tr><td>B-6-B(V_7)</td><td>34</td><td>40</td></tr>
<tr><td>Total Distance</td><td colspan="5">**39+119=158**</td></tr>
<tr><td rowspan="7">2-Depot using
C&W</td><td rowspan="5">Depot-A</td><td>A-6-12-A(V_1)</td><td>36</td><td>65</td><td rowspan="5">93</td></tr>
<tr><td>A-8-10-A(V_2)</td><td>20</td><td>60</td></tr>
<tr><td>A-1-9-A(V_3)</td><td>22</td><td>65</td></tr>
<tr><td>A-11-13-A(V_4)</td><td>13</td><td>70</td></tr>
<tr><td>A-3-A(V_5)</td><td>2</td><td>45</td></tr>
<tr><td rowspan="2">Depot-B</td><td>B-4-5-B(V_6)</td><td>25</td><td>50</td><td rowspan="2">39</td></tr>
<tr><td>B-2-7-B(V_7)</td><td>14</td><td>80</td></tr>
<tr><td>Total Distance</td><td colspan="4"></td><td>**93+39=132**</td></tr>
</table>

DISCUSSION AND CONCLUSION

From the above Fig 10, distance travelled by different vehicles based on routing done using various algorithms and for multiple depots are given and from that we can analyze that there is a rapid savings in the distance travelled on introduction of new depots. On introduction of new depots there will be increase in Variable costs like maintenance costs, labor costs, rent for the warehouses and various other costs which are to be taken into consideration while selecting the best and optimum solution from the available feasible solutions. Here we have savings of 62 kms per day for 2-Depot and 76 kms per day for 3-Depot when compared with the results of Single depot. Also 2-Depot VRP uses 7 vehicles to meet the daily requirements whereas 3-Depot VRP uses 8 vehicles per day which adds up cost to the company despite savings of 14 kms per day than 2-Depot VRP. Also there is a requirement of establishing extra warehouse if we introduce 3-Depots.Hence when we compare all the costs that adds up externally in in introducing Multi Depots therefore we came to a conclusion that 2-Depot Vehicle Routing Problem is the optimal solution for this city.

After finding the optimal number of depots we now compare the results of 2-Depot Vehicle Routing Problem solved using Heuristic Algorithm with a Meta Heuristic Algorithm i.e. Ant Colony Optimization from which we can observe that results obtained from Clarke and Wright Algorithm proves to be better than Ant Colony Optimization. From the various research works we came to know that Meta heuristics plays a vital role in finding out the optimal solution. But in our work Clarke & Wright Algorithm came up with a better solution due to its greediness and robustness. The importance of Meta heuristics comes into play when the large area of interest is being considered. Although heuristic algorithm gave us better result, when the area of interest becomes larger it is very much difficult to solve using Heuristics as they make the problem much complex. Hence we can say that there is no particular or single algorithm that gives an optimum solution all the time. It purely depends on the constraints prevailed. Hence there is much scope for research in the area of Vehicle Routing Problems.

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