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Complexities in Dynamic Vehicle Routing Problem & Survey of DVRP Algorithms

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ABSTRACT: The Vehicle Routing Problem (VRP) was formulated by Dantzig and Ramser who was trying to solve the problem of delivering gasolines to service stations. They used a mathematical and algorithmic approach. Vehicle Routing Problem is popularly called as VRP which is NP hard combinatorial optimization problem It can be solved exactly for small instances. We can use heuristic approach to solve the problem which generally gives best result practically. A New methodology in research called the meta-heuristics has emerged to solve the problem of VRP. In this paper, we see the complexities of Dynamic Vehicle Routing Problem & the algorithms used for solving them.

KEYWORDS: DVRP, Heuristics Method, Large Neighborhood Search, ACS, cross over

I. INTRODUCTION

In the static Vehicle Routing Problem (VRP) the total travel time or the total number of customers are known priori. In static VRP is devised as minimum cost problem where a fleet of vehicles have to visit a set of with in a stipulated amount of time.

In Dynamic Vehicle Routing Problems (DVRPs) the new orders arrive dynamically after the fleet of vehicles have started their tours. To include these new orders the route has to be re planned at run time. First we consider a set of orders which are known in earlier and a first schedule is calculated for it. When the new orders are received during tour execution and the tours have to be rearranged. In most of the DVRP problem types the orders received after a given time is postponed to the next day.

A number of technological advancements today have led to the multiple real time applications with GPS(Global Positioning System) & GIS(Geographic Information System). The companies have been able to track & manage their fleet in real time and effectively.

Traditionally we follow, **Plan & Execute (two step process)** which gives the opportunity to reduce operational costs, improve customer service and reduce environmental (real world) impact. Here generally we come across **"immediate requests"** which need re planning of the routes & vehicles fleet.

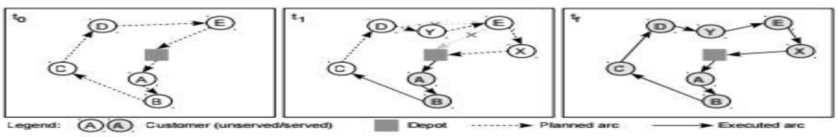

Figure 1: Example of dynamic vehicle routing

its next request (second double-headed arrow).

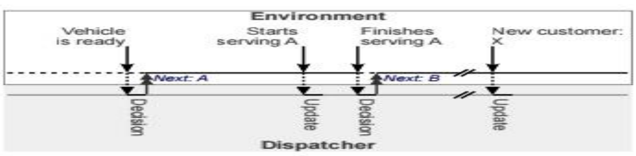

Figure 2: Timeline of events for the dynamic routing of a single vehicle

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II. COMPLEXITIES IN DYNAMIC VEHICLE ROUTING PROBLEMS

In most of the applications we see that the new orders arrive which has to be allocated to the vehicles. The vehicles may have left the depot. For example, Air cargo Services, parcel collection & distribution, fuel distribution, transport of goods, Transport of people, feeder systems etc.

In most of the above real time applications all the transportation requests may not be known during the load acceptance and planning of services starts. When the requests starts coming in when already the vehicles have left the depot, sometimes the requests have to be allotted to already departed vehicles or it should be allotted to new vehicles using the make-or-buy decision policy.

The transportation request will have to be served by a specific vehicle which is assigned with the given set of requests with time windows to serve different locations. The revenue generated after the service may sometimes be considered or not.

Some of the transportation requests also as further complexities which are dependent on their capacities and compatibility constraints. Further there are constraints on where the shipments will have to be loaded and unloaded.

So, for the dynamic vehicle routing problems we can have various time constraints, capacity requirements,
Scheduling strategies based on time, load and location factors.

The vehicles can start from one of the locations and before it returns to its depot it may have to do several trips which has to be completed in a specific time window.

If the vehicle reaches its location before the specified time it may have to wait before the shipments are loaded or unloaded.

The drivers may have to be given rest periods between the trips after a specific number of tours. The tour is feasible only if all the constraints hold good with the compatibility constraints, time window constraints and the delivery of the orders. The objective of dynamic vehicle routing problems is to find distinct feasible tours by accumulating the revenues generated by serving all the requests and maximizing the profits and thereby reducing the costs of executing the requests.

III. ALGORITHMS USED IN DYNAMIC VEHICLE ROUTING PROBLEMS (DVRP)

We mainly observe three types of algorithms in Dynamic Vehicle Routing Problems. They are:

1) **ACS (THE ANT COLONY SYSTEM) -**The decomposition of the DVRP into a sequence of static VRPs. There are three main elements in the architecture we propose.

1.1) **Event manager-** The event manager keeps track of new orders and also information about the served orders.It also keeps track of the capacity of the vehicles. For each set of specific orders the static VRP is constructed and the vehicles are allotted. Every working day is divided into various time slices and the static VRPs are assigned to it which are not yet executed**.** Any new orders received are put in the end in a new static VRP which will be executed after the current orders are served in the next static VRP.

1.2) **ACS algorithm -** The Ant Colony System (ACS) algorithm is inspire by the way the real ant colonies work. (see Dorigo et al. [1]). Ants uses different mode of communication to show the shortest paths to the food using pheromone trails. Ants lays pheromone on the ground, while it searches for the food by creating a path for other ants searching the food. Other ants which follows this can decide with great probability its path and also reinforces the path. This process continues with other ants and creates a positive feedback loop which emphasizes the use of the path more by other ants. The ACS is inspired by this process. It is applied to the static VRPs created from a DVRP. The method is similar to that described in Gambardella et al. [2], which solves the VRP with time windows very efficiently. In the algorithm, the ants are used as elements which are simple computational agents which iteratively constructs the solution for the problem. During each step the ant constructs a partial probable solution of visiting each customer in the sequence and also justifying the path taken. It adds new edges to the solution path and also verifies that the path taken earlier are part of the "good" optimistic solution.

1.3) **Pheromone conservation-** The pheromone matrix consists of the good solutions for the relative static VRP and for the specific time slice. This information is passed to the next problem.

2) **LARGE NEIGHBORHOOD SEARCH (LNS) WITH TIME WINDOWS-** It uses the Iterated Local Search method introduced by M. Gendreau et al [4]. The method starts with an initial solution s. In every k iteration, the

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transportation requests are removed from their tours in the current solution s. A new solution s∗ is then generated by inserting unscheduled transportation requests. The new solution is accepted for the next iteration as solution if the objective value is improved. We can adjust the number of removals before we start the next iteration. The algorithm continues with the next iteration if the termination condition is not satisfied.

LNS algorithm
1. s: = initialsolution()
2. s0: = removeorders(s, k)
3. s∗: = insertorders(s0)
4. if s∗ is better than s set s: = s∗
5. adjust parameters
6. goto 2 or stop.

LNS is well suited for the VRP with several additional constraints. To ensure very fast response times we propose two fast insertion methods. The first method is a sequential insertion method. In this method, all the unscheduled transportation requests are considered and all the feasible and efficient insertion possibilities are calculated. The incremental cost is calculated as infinite if no feasible solution is possible. The incremental cost is smaller than the revenue of the order. If any efficient insertion is possible than that is inserted in the tour with high efficiency.

The second insertion method is based on the auction method. This method is illustrated in figure3. In the first phase, all unscheduled orders requests are received from each vehicle. In the second phase, each unscheduled order chooses a vehicle with low incremental costs and sends a proposal for insertion to this vehicle. In phase three, each vehicle is ordered in such a way that the received proposals are inserted into the tour optimally. The method stops if no order can be efficiently inserted and continues otherwise.

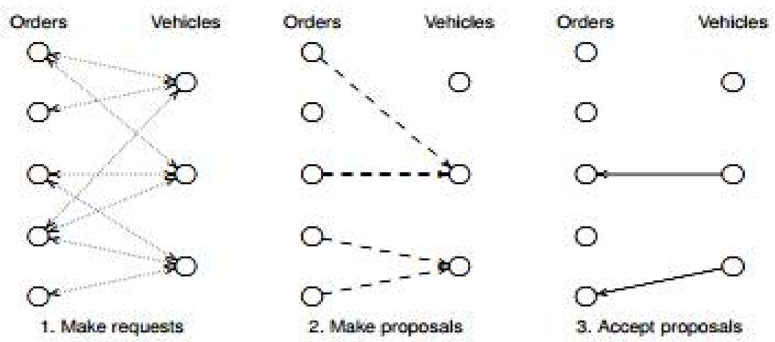

Figure 3. Illustration of the Auction Method

In step 1 of the LNS algorithm [4] propose transportation requests for unscheduled requests randomly for the requests which are related to each other geographically nearer to each other.

3) **MULTI-OBJECTIVE GENETIC SEARCH FOR THE VRP-** This method is also known as Multi-objective optimization or multi-criteria optimization method. In this method two or more conflicting objectives are simultaneously optimized subject to constraints. In this type of problem there cannot be one single solution when various constraints have to be worked out. Here each objective is optimized to its maximum extent so that further optimization affects other objectives. The goal of this method is to find a better solution and to compare it with other solutions and to prove how much it is better than the earlier solution. In Genetic Algorithm, clusters of routes are formed with chromosomes selected from the population pool. These chromosomes are subjected to an iterative evolutionary process until a minimum possible number of route clusters is attained or the termination condition is met. The evolutionary part is carried out as in ordinary GA using selection, crossover, and mutation operations on chromosomes. The individuals are selected for reproduction based on their fitness tested during a process called as

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Tournament selection Process. A crossover operator that ensures solutions generated through genetic evolution are all feasible is also proposed. Hence, both checking of the constraints and repair mechanism can be avoided, thus resulting in increased efficiency.

3.1. Chromosome Representation and Initial Population Creation- Here a chromosome representing a route of length N, where N is the number of customers in a particular problem instance. A gene in a given chromosome indicates the original node number assigned to a customer, while the sequence of genes in the chromosome indicates the order of visitation of customers, * indicates a node representing a group of clustered customers that have already been committed to a given vehicle. Thus, the chromosome consists of integers, where new customers are directly represented on a chromosome with their corresponding positive index number and each committed customer is indirectly represented within one of the groups (shown by a * mark) representing a given deployed vehicle.

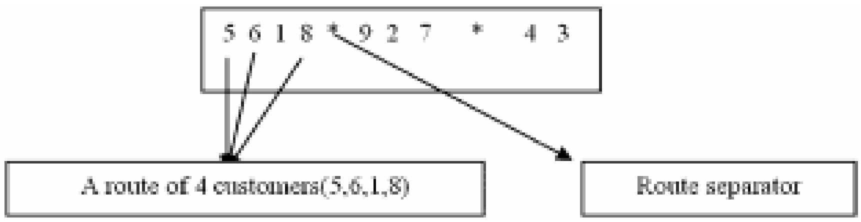

Figure4.Chromosome representation

3.2. Fitness Evaluation The fitness of a chromosome is determined after each chromosome has been transformed directly into a route network topology.

$$f(x) = \sum_{(i,j)\in ri, ri\in R} \alpha\, d_{ij} + \beta(|V| - V_{min}) \qquad (1)$$

where α and β are weight parameters associated with the number of vehicles and the total distance traveled by vehicles respectively. The weight values of the parameters used in this function were established empirically and set at $\alpha = 0.01$ and $\beta = 100$. In the above expression dij is the distance from node i to node j, r i is the sub route of the route R, V is the total no. of vehicle of the route. Vmin is the minimum no. of vehicle per route. It is calculated as

$$V_{min} = \frac{\sum_{i=1}^{n} demand_i}{\text{Capacity of vehicle}} \text{ where, i is the customer}$$

From 1 to n.

3.3. Cross Over Initial experiments using standard crossover operators such as Partially-Mapped-Crossover (PMX) and uniform order crossover (UOC) yielded non-competitive solutions. Hence, we utilized a problem-specific crossover operator that generates feasible route schedules. An example of the procedure utilized by the proposed crossover (Best-Cost Route Crossover, BCRC) is given in Fig. 5. Two parents A and B are selected from the population. For each parent chromosome, a route is selected randomly and the customer orders present in each route are removed from the other parent. Since * marks represent existing vehicles, their customers are left untouched. This means only integers which represent uncommitted customers are reinserted into the current chromosome. Then the customers that have been removed are reinserted at the location which minimizes the overall cost of the entire tour. Without violating the constraints, the cost of inserting the remaining customers will have to be computed. If no insertion location for a particular customer is found, a new route is created.

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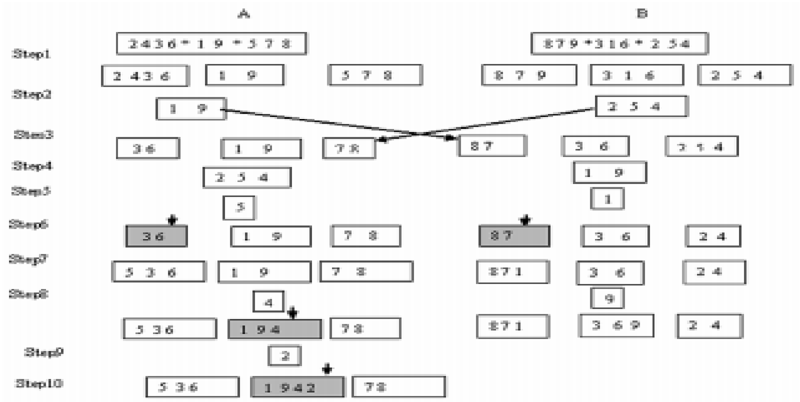

Figure 5. Best Cost Route Cross Over

Mutation is done by doing swap mutation. Select any two customers from any two route randomly and exchange their position if satisfying all the constraints. After swap, insertion is done in which we select randomly a customer from a route and try to insert rest of any one route if it satisfies all the constraints.

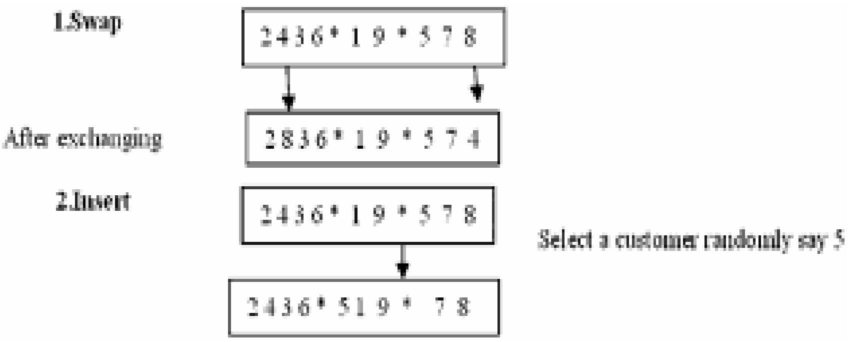

Figure 6. Mutation

IV. CONCLUSION

In this paper, we have surveyed the complexities of the Dynamic Vehicle Routing Problem and seen several algorithms used in real time. Some of these algorithms also use heuristics methods. There is lot of scope to develop new algorithms which is faster, efficient and feasible.

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BIOGRAPHY

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