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RESEARCH ARTICLE

A BRIEF OVERVIEW OF VEHICLE ROUTING PROBLEM AND TWO-PHASE HEURISTICS

Siddharth S¹ and Nandini B²

1. Student, Department of Industrial Engineering and Management, R V College of Engineering, Karnataka, India.
2. Assistant Professor, Department of Industrial Engineering and Management, R V College of Engineering, Karnataka, India.

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Abstract

This article provides a comprehensive introduction about the Vehicle Routing Problem and the Two-Phase heuristics used to solve the routing problem. First, the paper gives an introduction to the Vehicle Routing Problem and its many popular variants. Then the approaches to solve the vehicle routing problem is described briefly. The next section defines heuristics and the criteria to be considered while selecting a heuristic, and the following section provides an overview on the classification of the heuristics used in vehicle routing problem. Several algorithms that utilize two phase heuristics are described in detail. Lastly the effectiveness of the two-phase heuristics is highlighted. The information and the review in this paper provides a clear overview of the Vehicle Routing Problem and its solution that employ two-phase heuristics, which can be used as a starting point for further research.

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Introduction:-

Routing is the method of finding paths from origin to destination in a transport network. For a transportation solution, this is one of the crucial tasks to use resources optimally. Routing is done such that the shortest path between the source and destination is selected to optimize the solution. Still, routing is not as simple as it sounds, as there are many underlying factors to consider that significantly influence the routing. Transportation and routing problems are usually solved based on Vehicle Routing Problem. The vehicle routing problem (VRP) is an optimization and mathematical integer programming problem which upon solving tries to generate the best set of routes possible for a fleet of vehicles to ply through to serve and deliver to a given set of customers [1]. It generalises the well-known travelling salesman problem (TSP). A vehicle routing solution is a set of ordered customer sequences. Each arranged series of points or nodes is called a route. A depot is located in a geographic region where a fleet of vehicles serves delivery requests, each assigned to a single route.

Review Of vehicle Routing Problem:

The Vehicle Routing Problem can be defined more formally as consisting of [2] : Inputs where:

1. A set of locations C is considered.
2. K number of vehicles are available in the depot.
3. And the cost of travelling from a location i to location j .
4. Are given. And the following assumptions are made regarding the problem:
5. The fleet of vehicles available is homogenous. That means all the vehicles in the fleet are of the same size and capacity.

Corresponding Author:-Siddharth S

Address:-Student, Department of Industrial Engineering and Management, R V College of Engineering, Karnataka, India.

6. The depot is denoted by two nodes, node 0 and node $n+1$.
7. The constraints placed on the model are:
8. The starting node of each route should always be a depot, and after visiting a subset of nodes, the route should terminate at the depot.
9. Each node can be visited exactly once in any given route.
10. Each and every vehicle in the fleet has a maximum carrying capacity of Q , restricting the number of nodes it can serve before returning to the depot. Each node has a stated demand of q_i , such that $q_i > 0$ for each i in C and $q_0 = q_{n+1} = 0$.

And the output obtained from the model is a route scheduled for the entire time period with the locations to be visited, the order in which they need to be visited, and the vehicles assigned to visit each location.

Variants Of The Vehicle Routing Problem Model And Their Literature:

The solutions to these routing problems can be modelled along with Vehicle Routing Problem (VRP) and its many variants. The vehicle routing problem (VRP) can be described as a more general version of the well-known travelling salesman problem (TSP). The VRP aims to construct a set of shortest routes for a fleet of vehicles of fixed capacity. Each node in the customer set is visited exactly once by only one vehicle, which delivers the demanded amount of goods. Each route has to start and end at a depot, and the sum of the visited customers' demands on a route must not exceed the vehicle's capacity. Another common constraint is that the customer may specify time intervals for deliveries. This additional restriction leads to what is known as the vehicle routing problem with time windows (VRPTW).

Another variant of VRP is the capacitated vehicle routing problem (CVRP). The capacity-constrained vehicle routing problem (CVRP) [3] is a VRP problem in which vehicles with limited carrying capacity is required to pick up items or deliver items at various customer locations. The items have a defined quantity, in terms of weight or volume, and the vehicles have a defined maximum capacity that it can carry. The problem in CVRP is to pick up or deliver the items for the least possible cost, while not exceeding the carrying capacity of the vehicles in the fleet.

Other variants of VRP include Vehicle Routing Problem with Pickup and Delivery (VRPPD)[4], where several goods are required to be transported from specific pickup locations to other delivery locations. The aim is to find the most favourable routes for a fleet of vehicles to visit the pickup and drop-off locations.

VRP with Multiple Trips (VRPMT) [5] is one more variant of VRP, where the vehicles can do more than one route. Open Vehicle Routing Problem (OVRP) [6] is another variant of VRP, where the vehicles are not required to return to the depot and so on. CVRP and VRPTW are the most common types of VRP, and extensive research and literature are available for these topics.

Solution Approaches for The Vehicle Routing Problem:

The VRP is known to be an NP-Hard problem, and heuristics often solve it except for minimal problems. Literature and their solutions approaches can be classified as follows [7]:

1. Mathematical Modelling (Exact Techniques)
2. Heuristics
3. Meta-heuristic
4. Interactive approaches
5. Hybrid Approaches (Combination)

Mathematical Modelling (Exact Techniques):

Mathematical modelling is a formulation, or an abstract representation of a system based on mathematical terminology to analyze the effects and influence of different constraints and components and, consequently, to make predictions. In this approach, one is inclined to suppose that it's capable of providing exact solutions. Sadly, even for a TSP and VRP of modest size, it is computationally too complex to solve.

Heuristics:

A heuristic technique, or a heuristic, is any approach to problem-solving that employs a practical method for reaching an immediate goal. As in the instance of other combinatorial problems, heuristics methods are generally

used for solving TSP and VRP. Heuristics restrict their exploration of the solution search space but aim at producing the right solution in a reasonably short time.

Meta-heuristics:

In meta-heuristics, the emphasis is on performing an in-depth exploration of the most promising regions of the solution space. These methods typically combine sophisticated neighbourhood search rules, memory structures, and recombination of solutions.

Interactive approaches:

These are straightforward approaches that can be tweaked to suit a particular application. It is usually based on intuition, simulation, preference, or some type of graphics to aid the decision-maker in a 'what if' mode.

Hybrid Approaches (Combination):

Analysts have also attempted hybrid approaches, combining two or more of those suggested in the preceding paragraphs. Some of these have been observed to have a high potential to provide excellent solutions at a low computational time.

Heuristics:

A heuristic is an approach to problem-solving that employs a practical method for reaching an immediate goal. Because of the difficulty of the VRP and its vast practical importance, there is a unique need to build algorithms capable of producing the right distinct solutions in brief computing times. Heuristics are also used to provide upper bounds for the exact algorithms [8].

Criteria for Heuristics considering VRP: VRP heuristics, like most heuristics, are usually compared against four criteria: accuracy, speed, simplicity, and flexibility.

Accuracy:

Accuracy gauges the extent of deviation of a heuristic solution from the best or optimal value. As optima and sharp lower bounds are usually unavailable in the case of the VRP, and mostly compared to the best-known parameters. However, analyzing and studying heuristic results is difficult. Authors often record results obtained for the best combination of algorithmic parameters and values or the best of several iterations, starting with different solutions. Also, as a convention, users prefer a heuristic that performs all the time sufficiently over a heuristic that may perform most of the time exceptionally but very poorly on other occasions. They may also produce solutions easily perfectible by visual inspection.

Speed:

Just how vital is computation speed in vehicle routing? It depends on the level of planning at which the problem is solved and how accurate of a solution is required. At one end of the spectrum is the real-time applications such as express courier pickup and delivery or ambulance redeployment require fast, sometimes almost instantaneous, action. For example, a quick response can be described as the crucial role of parallel computing in a scenario where an ambulance movement strategy must be determined every three minutes. At the other end of the spectrum is the long term and permanent planning decisions that are made every several months, such as fleet size estimation, it is reasonable to invest long periods of time up to several days of computing time, more so if a significant capital is at stake. Most applications fall somewhere between these two ends of the spectrum. For routing problems that are to be solved daily, it is reasonable enough to invest several minutes of computing time.

Simplicity:

Several VRP heuristics are rarely implemented because they are just too complicated to understand and to code. While it is unrealistic to expect scientific articles to provide a minute description of every algorithmic detail, sufficient information should be mentioned to enable a reasonably skilled programmer to come up with a working code. Also, heuristics should be justifiably robust to ensure that they work correctly, even if not every single detail is implemented. Most algorithmic descriptions fail on the count of giving excessive or inadequate detail. Simple codes, preferably short and self-contained, stand a better chance of being adopted, although, for good results, a minimum of complexity is to be expected. Algorithms that contain too many parameters are considered to be challenging to comprehend and doubtful to be used. This dilemma is prevalent in most metaheuristics developed over the past decade.

Flexibility:

A useful VRP heuristic should be flexible enough to accommodate the various side constraints encountered in a majority of real-life applications. While most of the VRP literature focuses on capacity and sometimes route length constraints, it is often clear how changes can be made to deal with additional restrictions, but this is not always possible. Performance can also deteriorate significantly as a result. A competent way of handling side constraints in a local search procedure is often recommended through the use of two objectives. The first objective, $F(x)$, computes the routing cost of solution x . The second objective, $F'(x)$, is the sum of $F(x)$ and weighted penalty terms associated with violations of each side constraint. Another algorithmic advantage of this device is that the search can be executed with relatively easy moves, like removing a customer from its current route and inserting it in a different route. So, in a sense, algorithmic flexibility is, in part, achieved through simplicity of design.

Classification of heuristics concerning vrp:

Heuristics can be broadly classified into three groups: Route construction heuristics, Route improvement heuristics, and Two-phase heuristics.

Route construction heuristics:

Route construction methods were one of the first heuristics developed for the VRP and still form the centre of numerous software and product implementations for many routing applications. These algorithms normally start from an empty solution and iteratively construct routes by inserting one or multiple customers at each iteration, till every customer is routed. Construction algorithms are additionally split into sequential and parallel, depending on the number of feasible routes for the insertion of a customer. Sequential methods expand to only one route at a time, whereas parallel processes compare multiple routes simultaneously. Route construction algorithms are completely specified by their three fundamental ingredients, namely an initialisation criterion, a selection criterion that determines which customers need to be chosen for insertion at the present iteration, and lastly, an insertion criterion to figure out where to locate the chosen customers into the existing routes.

Route improvement heuristics:

To improve initial solutions developed by other heuristics, local search algorithms are used. Starting from a given initial solution, a local search method performs simple adjustments, such as arc exchanges or customer movements, to obtain neighbour solutions of possibly better cost. If an improving solution is found, it becomes the current solution, and the process iterates; otherwise, a local minimum has been identified.

Two-phase heuristics:

The two-phase method is based on breaking down the VRP solution process into the two separate sub-problems:

1. Clustering: to establish a partition of the customers into clusters or subsets, where each cluster or subset corresponds to a route.
2. Routing: to establish the order of customers on each route.

There are two types of two-phase heuristics:

Route first, cluster-second procedure: This procedure starts with a huge route, which is often infeasible, and partitioned to smaller clusters. We first form a 'giant tour' from the depot around all the customers and back to the depot (i.e., a travelling salesman tour around all the customers, including the depot). The key to the approach is that it is simple enough to optimally partition such a tour into a set of feasible vehicle routes, but the performance of this approach is generally poor.

Cluster-first, route-second procedure:

Cluster the nodes and determine feasible routes for each cluster; this is the principle of this approach. In this methodology, the initial problem is decomposed into smaller sub-problems by first clustering customers into groups whose total demand does not exceed the capacity of the vehicle. Second, the customers in each of these groups are routed. The routing of these clusters is the well-known travelling salesman problem (TSP). Various techniques have been recommended for the clustering phase, whereas for the routing phase, it just boils down to solving a TSP. Our focus is concentrated on this procedure as this more has opportunities for application.

Several algorithms That Utilize Two-Phase Heuristics:

Some of the algorithms that follow cluster-first, route-second procedure are but not limited to:

The sweep algorithm: The sweep algorithm is often referred to as the first example of the cluster-first, route-second heuristic [9]. The algorithm applies to planar VRP instances, i.e., VRP limited to two-dimension. The algorithm commences with a random customer node and then successively assigns the remaining customers to the current vehicle by comparing them in order of increasing polar angle considering the depot and the initial customer. When a current customer cannot be assigned to the current vehicle, a new route is generated with it. When all the customers are assigned to vehicles, each route is separately defined by solving a TSP.

Another fundamental two-phase method is the truncated branch-and-bound method of Christofides [10], where the set of possible routes is ascertained through an adaptation of an exact branch-and-bound algorithm that utilizes a branching-on-routes strategy. A branch-and-bound algorithm comprises a systematic identification of candidate solutions utilizing state-space search: the set of candidate solutions is thought of as developing a rooted tree with the full set at the root. The algorithm searches branches of this tree, which represent subsets of the solution set. Before identifying the candidate solutions of a branch, the branch is checked against the upper and lower estimated bounds on the optimal solution. It is discarded if it cannot produce a better solution than the best one found so far by the algorithm. The algorithm relies on the efficient estimation of the lower and upper bounds of branches of the search space. If any bounds are unavailable, the algorithm degenerates to an exhaustive search. The decision tree contains the same number of levels as the number of available vehicles. At every decision tree level, a given node amounts to an imperfect solution consisting of a few complete routes. The descendant nodes correspond to all feasible routes, including a subset of the unrouted customers. The run time of the algorithm is controlled by limiting the number of routes generated at each level.

The Fisher and Jaikumar algorithm [11]: The Fisher and Jaikumar algorithm solve the clustering step utilizing an appropriately defined Generalized Assignment Problem (GAP). In the generalized assignment problem, both jobs and agents have a size. Moreover, the size of each job varies from one agent to the next. In its most general form, the GAP problem is as follows: There are several agents and many jobs. Any agent can be allotted to complete any job, incurring some cost and profit that may vary depending on the agent-job allocation. Furthermore, every agent has a budget, and the sum of the costs of tasks allotted to the agent cannot exceed this budget. The essential problem is to find an assignment in which all agents are well within their budget, and the total profit of the assignment is maximized.

GAP requires the determination of a least-cost assignment of items to a given set of bins of capacity Q . The items are characterized by the weight or volume and an assignment cost associated with each bin. Similarly, each vehicle is assigned a representative customer called a seed, and the cost associated with the assignment of the customer to a vehicle is equal to its distance to the seed. The GAP is then solved, heuristically or optimally, and the final routes are determined by solving a TSP on each cluster. The Fisher and Jaikumar algorithm is not simple to program, and its speed is highly related to the choice of seeds and the implementation of the Lagrangian process.

Bramel and Simchi-Levi two-phase method [12]: Bramel and Simchi-Levi described another two-phase method working with a fixed m number of vehicles. The Bramel and Simchi-Levi algorithm identify route seeds by solving a capacitated location problem, where m number of customers are selected by reducing the total distance between each customer and its closest seed, and by constraining the overall demand associated with each seed can only be at most Q . When the seeds have all been identified, and the single/individual-customer routes are initialized, the remaining customers are then inserted in the current routes such that the insertion costs are minimized. It is worth noting that of all the four cluster-first, route-second methodologies described above provides direct control over the number of routes generated in the final solution, whereas the sweep algorithm does not provide such control. The performance of these algorithms is typically comparable to that of route construction algorithms in terms of effectiveness. The location-based approach of Bramel and Simchi-Levi produces better solutions but requires much larger computing times. When all the customers are assigned, the order of the route is solved by TSP.

Petal algorithm [13]: A different family of two-phase methods is the class of so-called petal algorithms. It is a natural extension of the sweep algorithm. Petal algorithm can be explained by picturing a central depot and several delivery points. The petal algorithm aims to minimize the number of vehicles required to deliver from a central depot, and for that number of vehicles, to reduce the total distance travelled. Each vehicle has a capacity of n units of demand. The delivery points are then categorized in radial order from the depot. Each radially spreading subset taken from this ordering is called a petal. A petal is possible only on two conditions, one, when the quantity of items or goods delivered on the generated route is not more than the capacity of the vehicle and two if the total distance

travelled, as determined by the Travelling Salesperson methodology for the sequence of deliveries, does not exceed the specified distance limit. We will call such a TSP route for a petal route and refer to it as feasible if the petal itself is viable. These generate an extensive set of possible routes, called petals, and select the final subset by solving a set partitioning model. The overall performance of this algorithm usually is superior to that of the sweep algorithm.

Conclusion:-

The goal of two-phase heuristics is to provide the best possible solution to the given vehicle routing problem. Due to the competitive and complex nature of businesses, companies and analysts are continuously looking for ways to gain the competitive edge by improving their efficiency, speed, and quality of the solutions that they generate. To this effect, two-phase heuristics can be utilized to generate quick and optimal solutions to the routing problem. Heuristics localize the search by imposing the constraints defined by the analyst or the user, to prevent searching the entire solution space and decrease the computation time or the execution time. Whereas exact methods and mathematical models search the entire solution space for every possible solution and then generate the optimal solution, this requires more computation time, which is not desirable. The two-phase heuristics are easy and simple to implement and maintain and hence does not require technological or mathematical expertise. Also, the two-phase heuristics can be implemented on any computer with average computational powers and a connection to the internet and does not call for expensive technology as is the case for most of the other solution approaches. Two-phase heuristics provides for precious savings in cost and time which in turn translates to competitiveness.

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