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Applications of Adaptive Search Techniques in Vehicle Routing based problems

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ABSTRACT

Research in the field of vehicle routing is often focused on finding new ideas and concepts in the development of fast and efficient algorithms for an improved solution process. Early studies introduce static tailor-made strategies, but trends show that algorithms with generic adaptive policies - which emerged in the past years - are more efficient to solve complex vehicle routing problems. In the first part of the survey, we presented an overview of recent literature dealing with adaptive or guided search techniques for problems in vehicle routing.

Keywords: Adaptive Techniques, Algorithms, Applications, Adaptive Strategies, Local Search, Variable Neighborhood Search, Vehicle Routing etc.

INTRODUCTION

Metaheuristics and vehicle routing problems (VRPs) are on the one hand, solution procedures and on the other hand, problem types which are strongly connected. Most of the VRPs are NP-hard and so efficient solution techniques do not exist, but in fact there are no adequate solution techniques for solving them. Therefore, these problem types are perfect applications where metaheuristic search techniques can provide substantial support in tackling them. In fact, with the invention of metaheuristic search a vast range of different VRPs could be solved in a reasonable manner. In the past years, many variations of the classical VRP were introduced and studied. The classical VRP has a central depot and a set of customers which have to be visited by a set of vehicles. Each vehicle has a certain capacity and it can also have a maximum tour length. Several variants of the classical VRP exist, e.g., VRPs with time windows (VRPTW) or open VRPs with (OVRPTW) and without time windows (OVRP). Also, different objective functions, different side constraints, and also different problem structures are considered. Due to the availability of data for the current traffic situation, the problems become even richer. The application area of VRP has many different problem settings, and therefore a large number of scientists are working on the development of different solution procedures. Although a number of different problem settings exist, some aspects of the problem characteristics are the same in many VRPs. This feature makes the applicability of generic search concepts possible. Nevertheless, it is not easy to find the appropriate search technique or the appropriate operator of a specific problem type. In the past years, adaptive search techniques where introduced to overcome the problem of selecting the most appropriate design decisions a priority.. Shortly after, one of the most popular construction heuristics for routing problems is introduced by Clarke and Wright ,the savings algorithm. Starting with single customer routes, routes are merged in a feasible way subject to maximize the cost savings. Few years later, the sweep algorithm is developed by Gillett and Miller . With this approach, routes are generated according to the polar coordinate angle of each node. At the time of the first calculating machines, the sweep algorithm was already seen as an efficient construction algorithm that competes with similar approaches. As computers influence the progress in approaches for VRP positively, learning mechanisms are included in search strategies as Ghaziri shows in. Artificial intelligence is used to learn from the previous performance of the algorithm by incrementally adjust their weights in an iterative fashion with mediocre success.

BASIC LOCAL SEARCH CONCEPTS

Since Tabu Search (TS) is a very popular algorithm based on local search, an important portion of the mechanisms described in this section are either based on TS or applied to TS. Before discussing adaptive strategies in TS, two general mechanisms of basic local search concepts, the reactive search (RS) and the guided local search (GLS), are described. RS is a general mechanism to adapt and tune the parameters of local search methods based on search history. General descriptions can be found in Battiti and Battiti and Brunato. An important idea of RS is to dynamically modify the behavior of a basic algorithm according to contextual needs in diversification or intensification. In the case of TS, both diversification and intensification are decided by the tabu tenure, also called tabu list size; therefore applying RS to TS requires to dynamically modifying the tenure. This is done, the tabu tenure is increased when previously visited configurations are repeated, thus providing extra diversification. If no previously visited configuration is repeated for some time, the tenure is decreased in order to rebalance the search towards more intensification. Additionally, when it occurs too often that previous states are revisited, an escape mechanism is triggered, which consists in performing random moves. Overall, this method could also be seen as ILS, which includes random moves fulfilling the role of perturbation.

The vehicle routing problem (VRP): VRP is a combinatorial optimization and integer programming problem which asks "What is the optimal set of routes for a fleet of vehicles to traverse in order to deliver to a given set of customers?". It generalises the well-known travelling salesman problem (TSP). It first appeared in a paper by George Dantzig and John Ramser in 1959, in which first algorithmic approach was written and was applied to petrol deliveries. Often, the context is that of delivering goods located at a central depot to customers who have placed orders for such goods. The objective of the VRP is to minimize the total route cost. In 1964, Clarke and Wright improved on Dantzig and Ramser's approach using an effective greedy approach called the savings algorithm.

Determining the optimal solution is an NP-hard problem in combinatorial optimization, so the size of problems that can be solved optimally is limited. The commercial solvers therefore tend to use heuristics due to the size of real world VRPs and the frequency that they may have to be solved.

The VRP has many obvious applications in industry. In fact the use of computer optimization programs can give savings of 5% to a company as transportation is usually a significant component of the cost of a product (10%) - indeed the transportation sector makes up 10% of the EU's GDP. Consequently, any savings created by the VRP, even less than 5%, are significant.

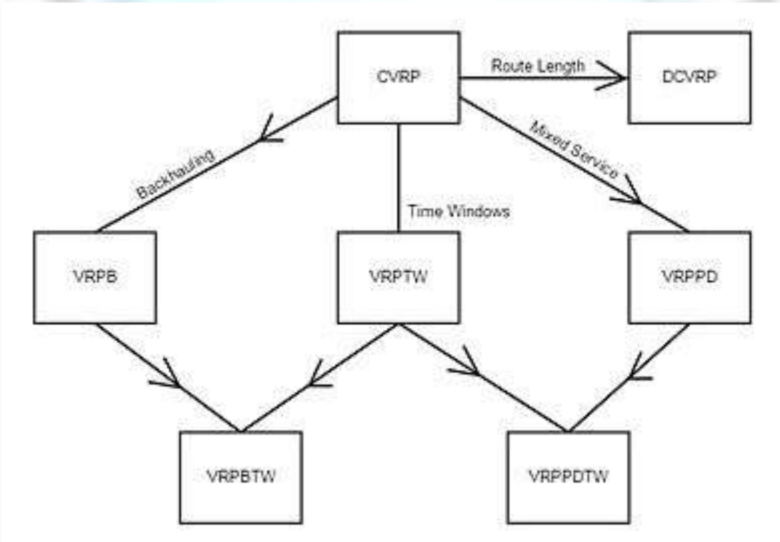

Fig 1: Relationship between common VRP subproblems.

VEHICLE ROUTING PROBLEMS (VRPS) VARIANTS

Several variations and specializations of the vehicle routing problem exist:

a) **Vehicle Routing Problem with Pickup and Delivery (VRPPD)**: A number of goods need to be moved from certain pickup locations to other delivery locations. The goal is to find optimal routes for a fleet of vehicles to visit the pickup and drop-off locations.

b) **Vehicle Routing Problem with LIFO:** Similar to the VRPPD, except an additional restriction is placed on the loading of the vehicles: at any delivery location, the item being delivered must be the item most recently picked up. This scheme reduces the loading and unloading times at delivery locations because there is no need to temporarily unload items other than the ones that should be dropped off.

c) **Vehicle Routing Problem with Time Windows (VRPTW)**: The delivery locations have time windows within which the deliveries (or visits) must be made.

d) **Capacitated Vehicle Routing Problem:** CVRP or CVRPTW. The vehicles have limited carrying capacity of the goods that must be delivered.

e) **Vehicle Routing Problem with Multiple Trips (VRPMT):** The vehicles can do more than one route.

f) **Open Vehicle Routing Problem (OVRP):** Vehicles are not required to return to the depot.

g) Several software vendors have built software products to solve the various VRP problems. Numerous articles are available for more detail on their research and results.

h) Although VRP is related to the Job Shop Scheduling Problem, the two problems are typically solved using different techniques.

Population-Based Methods

Adaptiveness can be also found in some population-based approaches. Interestingly, some population-based methods are adaptive by nature. This is the case with ant colony optimization and the methods based on the concept of adaptive memory programming. ACO relies on repetitively calling a probabilistic construction heuristic. At a given stage of this construction heuristic, solution components have a certain probability of being selected, this probability being influenced by a so-called pheromone value. This pheromone value is regularly updated based on search history and on the quality of solutions previously using the same solution component. When solving routing problems, such components are typically arcs. Arcs which have been present in good solutions have higher probabilities of being selected.

ACO is a constructive metaheuristic, therefore efficient solutions, have to be obtained. There is a significant literature on ACO methods for routing problem. The general idea behind adaptive memory programming is to keep a number of good solutions encountered during the search, and use this memory to build new solutions. Every time a new solution is built, the memory is adapted in order to integrate the new solution if necessary (that is, if it is interesting to add this solution to the adaptive memory). This memory can be seen as a pool or population of solutions, which is why we mention it here. Adaptive memory has been used to solve routing problems. For instance, develop an adaptive memory 24 S. Kritzinger, F. Tricoire, K. F. Doerner, R. F. Hartl / Adaptive Search Techniques methodology for the vehicle routing problem with simultaneous pickups.

Large Neighborhood Search (LNS)

The LNS is a specialization of the concept of local search to so-called large neighborhoods. In LNS, the neighborhood considered is the set of solutions that can be obtained by destroying large portions of an incumbent solution x, and then repairing this partial solution to make it a feasible solution to the whole optimization problem at hand. The terms destroy and repair can be substituted with ruin and recreate. Since there are many ways of destroying and repairing a solution, the neighborhood is very large. Hence, it is explored heuristically and destroy and repair heuristics are designed for that purpose.

Then LNS consists in iteratively :

(i) selecting a pair of destroy and repair operators,

(ii) applying them to the incumbent solution, and

(iii) deciding to accept or not the new solution.

ALNS, introduced in Ropke and Pisinger , adds an adaptive mechanism to the step where the operators are selected, by using search history to favor the S. Kritzinger, F. Tricoire, K. F. Doerner, R. F. Hartl / Adaptive Search Techniques 19 most successful operators. Using the previously introduced notation and style, we outline ALNS in Algorithm 5. The algorithm has to be initialized with the construction of a starting solution x (line 1). At every iteration, a destroy operator d and a repair operator r need to be selected (line 4). The adaptive aspect of ALNS lies in the history parameter on line 4: without this parameter, the algorithm describes LNS. Then d destroys x and r repairs d(x) (line 5). A new solution x 0 is obtained. If x 0 passes the acceptance decision, it becomes the new incumbent. If the new incumbent improves the best found solution x ∗ then x ∗ is updated accordingly.

Algorithm 5 (Adaptive large neighborhood search).

1: x ← construction Heuristic()
2: x ∗ ← x
3: while stopping criterion not met do
4: (d,r) ← select Operators(history)
5: x 0 ← r(d(x))
6: if acceptance Decision(x, x 0 , history) then
7: x ← x 0
8: if z(x) < z(x ∗) then
9: x ∗ ← x
10: end if
11: end if
12: end while
13: return x ∗

A collection of recent and important ALNS contribution is summarized and a description of the destroy and the repair operators can be found in next one. Although the ALNS is introduced in Ropke and Pisinger, the mostly cited paper discussing ALNS is presented by Pisinger and Ropke. The algorithm is able to solve several variants of VRPs. The key to success of this unified framework is the strategy of choosing the destroy and the repair neighborhoods due to their success in the past. The Adaptiveness lies in a simple roulette wheel mechanism to update the probability for each operator to be chosen: the more successful an operator Ni is, the more its score xi is increased; the less contribution an operator Ni has, the less its score xi is increased. Scores are updated every time a time segment of 100 iterations is started. Information from past time segments is kept by updating the score parameters using the reaction factor $\rho = 0.1$. The probability P(i) for choosing operator Ni ∈ ω is calculated. The ALNS algorithm has also been applied to different research areas only with slight parameter changes. Furthermore, destroy and repair operators are previously treated independently, but recent trends, e.g. Kovacs et al. have shown that dependent considerations of neighborhoods pairs are efficient as well. The discussed ALNS is a competitive approach solving different variants of VRPs and obtaining new best solutions, e.g., for the VRP with time windows.

SOLUTION METHODS

There are three main different approaches to modeling the VRP:

1. **Vehicle flow formulations -** this uses integer variables associated with each arc that count the number of times that the edge is traversed by a vehicle. It is generally used for basic VRPs. This is good for cases where the solution cost can be expressed as the sum of any costs associated with the arcs. However it can't be used to handle many practical applications.

2. **Commodity flow formulations -** additional integer variables are associated with the arcs or edges which represent the flow of commodities along the paths travelled by the vehicles. This has only recently been used to find an exact solution.

3. **Set partitioning problem -** These have an exponential number of binary variables which are each associated with a different feasible circuit. The VRP is then instead formulated as a set partitioning problem which asks what is the collection of circuits with minimum cost that satisfy the VRP constraints. This allows for very general route costs.

CONCLUSION

This paper presents an overview of recent adaptive mechanisms when solving vehicle routing problems (VRPs) with metaheuristics. Starting with basic local search-based methods, e.g. adaptive tabu search (ATS) or guided local search (GLS), we progress to hybrid local search methods, e.g. iterated local search (ILS), adaptive variable neighborhood search (AVNS) and adaptive large neighborhood search (ALNS). For the sake of completeness, we concluded the survey with population-based methods, e.g. ant colony optimization (ACO), mimetic and genetic algorithms (GAs). The most popular and very successful adaptive approach is the ALNS using a clever selection mechanism favor the most successful operators. Also, recent work in population-based methods, e.g. Vidal achieve, by using, adaptive crossover and mutation rate competitive results. In order to further investigate which of the possible adaptive strategies are particularly useful, Part II of this survey will consider several ways of making a VNS algorithm adaptive and will investigate numerically, which ones are useful and promising for solving the open VRP instances.

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