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A New Hybrid Evolutionary Algorithm for the Vehicle Routing Problem with Time Windows

The purpose of this paper is to present a new method for solving the vehicle routing problem with time windows (VRPTW). A typical vehicle routing problem (VRP) can be described as the problem of designing least cost routes from one depot to a set of geographically scattered points (cities, stores, warehouses, schools, customers etc). The routes must be designed in such a way that each point is visited only once by exactly one vehicle, all routes start and end at the depot, and the total demands of all points on one particular route must not exceed vehicle capacity.

Vehicle routing problems are all around us in the sense that many consumer products such as soft drinks, beer, bread, snack foods, gasoline and pharmaceuticals are delivered to retail outlets by a fleet of trucks whose operation fits the vehicle routing model. In practice, the VRP has been recognized as one of the great success stories of operations research and it has been studied widely since the late fifties. Besides, being one of the most important problems of operations research in practical terms, the VRP is also one of the most difficult problems to solve. It is quite close to one of the most famous combinatorial optimization problems, the Traveling Salesperson Problem (TSP), where only one person has to visit all the customers. TSP is a NP-hard problem. It is believed that one may never find a technique that will guarantee optimal solutions to large problem instances given reasonable computational time. The VRP is even more complicated and therefore untractable. Even for small fleet sizes and a moderate number of transportation requests, the planning task is highly complex.

The vehicle routing problem with time windows (VRPTW) is a generalization of the VRP involving the additional constraint that every customer must be served within a given time window. Furthermore, the objective evolves to minimizing a combination of both traveled distance and total duration of individual routes. New complexities encountered in VRPTW formulation are itinerary constraints (maximum length of route) arising from depot time windows and, the cost of waiting which is incurred when a vehicle arrives too early at a customer location.

In this paper, a two-phase procedural approach is presented. In the first phase a genetic algorithm based on hybridization of well-known route-construction heuristics is used to obtain a feasible solution. In the second phase the solution is improved using a new evolutionary approach. Having a structure similar to genetic algorithms, the approach involves 6 different local search and route construction heuristics.

Genetic algorithms are a subclass with respect to evolutionary algorithms. The class of evolutionary algorithms comprises genetic algorithms, evolution strategies and evolutionary programming. Classical genetic algorithms work on a population of chromosomes that encode the characteristics of the corresponding individuals. However it is very difficult to encode multiple routes on a chromosome, and to design crossover operators that would generate feasible offspring at the coding level. Accordingly, hybrid genetic algorithm (HGA) used in the first phase of our method directly applies the genetic operators to solutions. The initial population for HGA is created with random heuristic that selects and inserts customers into routes in a totally random manner. The selection process consists of choosing two individuals (parent solutions) within the population for mating purposes. We use a roulette-wheel scheme. In this stochastic scheme the probability to select an individual is proportional to its fitness value. The calculated fitness values are based on number of routes and total traveled distance.

The crossover operators of the HGA are based on identifying and removing some customers that should suitably be located within some other route and replacing these customers with ones from nearest routes of the alternate parent solution. The mutation phase mainly emphasizes two strategies. On the one hand, it consists in eliminating routes having only a few customers and, on the other hand, eliminating related customers and trying to reinsert them into alternate routes.

In the evolutionary algorithm (EA) routes of the constructed solution are considered as individuals and crossover and mutation operators are applied directly to them. The selection is not based on fitness values. Instead all pairs of routes are considered in random order. Once a pair of routes is selected (parent routes), one out of the four local search operators or route construction heuristics designed for two routes (crossover operators) is applied randomly based on user-defined probabilities.

The crossover operators of the EA are based on swapping segments of varied size of consecutive customers between parent routes, on insertion of customers in random order into other routes, and on usage of cheapest insertion heuristic to insert customers into the best possible places in parent routes according to a certain evaluation measure. Offspring routes generated by these crossover operators are mutated according to a user defined probability. Mutation is specifically achieved by selecting randomly one out of two operators according to a user-defined probability distribution. One of the two mutation operators is based on Or-opt exchanges and it is used to reorder customers within each route. The other mutation operator focuses on customers who have several possible service orders and reinserts them into the route so that additional detour is minimized. Selecting each possible pair of routes based upon a random order, mating and mutation operators are repeatedly applied for a certain number of generations.

Finally the EA uses the principles of Guided Local Search (GLS) in trying to escape local minima. The basic principle of GLS is to penalize certain "bad features" in order to guide local search procedures. Here we penalize arcs longer than average.

Results are reported for the standard 100 node data sets of Solomon (1987). The findings indicate that the proposed procedure outperforms other genetic algorithms, and that the results are very competitive with the results of the best metaheuristics found in the literature. In addition, it is shown that the EA may significantly improve results obtained with our genetic algorithm. The proposed evolutionary algorithm may also be used as an efficient post-optimization technique in combination with a wide variety of VRPTW algorithms. Future research will explore usage of different diversification and intensification techniques in order to escape local minimum and to further reduce the number of routes.