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A knowledge-based evolutionary algorithm for the multiobjective vehicle routing problem with time windows

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ABSTRACT

This paper addresses the multiobjective vehicle routing problem with time windows (MOVRPTW). The objectives are to minimize the number of vehicles and the total distance simultaneously. Our approach is based on an evolutionary algorithm and aims to find the set of Pareto optimal solutions. We incorporate problem-specific knowledge into the genetic operators. The crossover operator exchanges one of the best routes, which has the shortest average distance, the relocation mutation operator relocates a large number of customers in non-decreasing order of the length of the time window, and the split mutation operator breaks the longest-distance link in the routes. Our algorithm is compared with 10 existing algorithms by standard 100-customer and 200-customer problem instances. It shows competitive performance and updates more than 1/3 of the net set of the non-dominated solutions.

1. Introduction

The Vehicle Routing Problem (VRP) aims to find the optimal set of routes for a fleet of vehicles to serve customers under specific constraints. In its basic form, the VRP involves a single depot as the start and end points of the routes. Each customer is associated with a location and a demand quantity. Each vehicle serves the customers along the designated route, and the total demand cannot exceed the maximum capacity. The VRP is a combination of two classical NP-hard combinatorial optimization problems, the bin packing problem and the traveling salesman problem (TSP). Similar to bin packing, solving the VRP requires partitioning customers into vehicles to minimize the required number of vehicles without violating the capacity constraint. For each vehicle, the VRP asks to find the lowest-cost (usually the shortest-distance) driving path, which is the same as what the TSP needs. The Vehicle Routing Problem with Time Windows (VRPTW) is an extension of the VRP. In the VRPTW, each customer has a predefined time window. A vehicle can start to serve a customer only within the time window. In this study, we take the time window as a hard constraint. If a vehicle arrives at the customer's location earlier, it must wait until the beginning of the time window; if the vehicle arrives later than the end of the time window, the solution is not acceptable. The VRPTW has many real-world applications, such as postal delivery, waste collection, school bus routing, and so on. Due to the challenging problem complexity and high practical value, the VRPTW is a very important research topic in the fields of operations research, transportation science, and computer science.

Several objectives have been considered in the VRPTW, and minimization of the number of vehicles and the total travel distance are the most common objectives in the literature. The classical way to address these two objectives is to minimize the number of vehicles first and then to minimize the total distance with the minimal number of vehicles. The number of vehicles is related to the investment of purchasing vehicles and the cost of hiring drivers; the travel distance, on the other hand, is related to the fuel cost. Optimizing the two objectives in the classical way implies that the vehicle-related cost is much higher than the distance-related cost. In many cases, however, fleet managers want to know the trade-off between these two objectives before determining the best routing plan. To accomplish this goal, another stream of research was started by searching for the set of Pareto optimal solutions rather than a single optimal solution. Hereafter, Pareto approaches refer to the approaches for which the goal is to find the Pareto set. The definition of Pareto optimal solutions and the Pareto set will be given in the next section. Simply speaking, solutions in the Pareto set are not worse than any other in both objectives simultaneously. By looking into the trade-off between these solutions, managers can get more information and make a better decision.

This paper proposes a knowledge-based evolutionary algorithm (KBEA) to solve the VRPTW. The remainder of this paper is organized as follows. Section 2 defines the target problem and the

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objectives. Section 3 gives the literature review. The proposed approach is elaborated in Section 4, and the experiments and results are detailed in Section 5. Section 6 draws the conclusions and provides future research directions.

2. Multiobjective Vehicle Routing Problem with Time Windows (MOVRPTW)

The VRPTW involves two types of objects: locations and vehicles. A special location 0 represents the depot. The remaining N locations correspond to N customers. For each customer i ($1 \le i \le N$), the demand q_i, the service time s_i, and the time window $[e_i, l_i]$ are known in advance. The travel distance and travel time between two locations i and j are denoted by d_{ij} and t_{ij}. (In this study, we assume that d_{ij} equals t_{ij}.) The vehicles are homogeneous and have the same maximum capacity Q. A feasible solution to the VRPTW must satisfy the following constraints:

(1) Each customer must be served by exactly one vehicle exactly one time.
(2) The route of each vehicle must start from and end at the depot.
(3) The total demand of the customers served by each vehicle cannot exceed the maximum capacity Q.
(4) A vehicle must arrive at customer i no later than the end of the time window: $a_i \le l_i$, where a_i denotes the arrival time at customer i.
(5) The service cannot start before the beginning of the time window: $b_i = \max\{a_i, e_i\}$, where b_i is the service start time at customer i.
(6) Assume that customer j is served immediately after customer i; then, the arrival time at j is defined by $a_j = b_i + s_i + t_{ij}$.

For each feasible solution, we calculate two objective values: the number of required vehicles and the total travel distance. We say that one solution x *dominates* another solution y if x is not worse than y in both objectives and is better in at least one objective. Taking Fig. 1 as an example, x dominates y, but x and z do not dominate each other. A solution is *Pareto optimal* if it is not dominated by any other solution. The set of Pareto optimal solutions is called the *Pareto set*, and the set of objective vectors of the Pareto optimal solutions is called the *Pareto front*. Take Fig. 1 as an example again. If we solve the VRPTW in the classical way (minimizing the number of vehicles and then the total distance), the fleet manager obtains a single optimal solution w; if we consider the total distance only, then the solution z is obtained. Compared with these two traditional approaches, the Pareto approach will output the Pareto optimal set of solutions $\{w, x, z\}$ to the manager. It offers the manager the opportunity of choosing solution x as the final plan based on the trade-off between two objectives that are of concern.

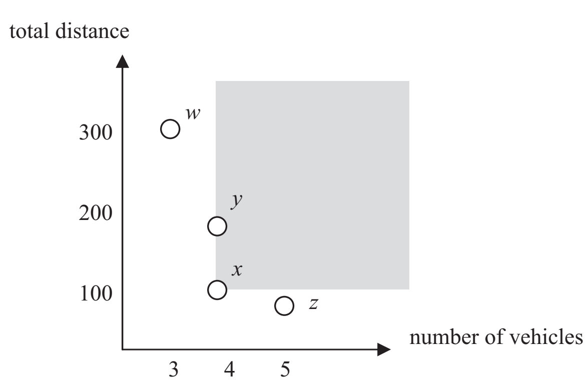

Fig. 1. Solutions to the MOVRPTW on the objective space (solution x dominates all of the solutions in the gray region).

3. Literature review

The NP-hard problem complexity means that currently no algorithm can solve the VRPTW optimally in polynomial time. In the literature, Jepsen et al. [23] could solve 45 out of 56 100-customer instances in Solomon's data set [38] optimally in terms of the total distance within hours. However, the exponentially growing computation time would limit the use of exact algorithms when the problem scale becomes larger and larger. Metaheuristics such as genetic algorithms (GA) and tabu search (TS) are promising approximation algorithms that have addressed hard optimization problems in recent decades. They have already demonstrated good performance in solving the VRPTW [9,34]. Here, we will focus on the literature that applies metaheuristics to solve the VRPTW. We classify the existing studies according to how they addressed the two objectives. Section 3.1 reviews the studies that minimized the objectives in the lexicographical way, and Section 3.2 reviews the studies that consider a minimization of the total distance only. Studies based on Pareto approaches are presented in Section 3.3.

3.1. Classical (lexicographical minimization) approaches

In the literature on the VRPTW, the classical way to address the two most common objectives is to minimize the number of vehicles and then to minimize the total distance with the minimal number of vehicles. This subsection will review past studies that belong to this category and describe the featured design concepts and techniques.

To cater to the lexicographical minimization of the two concerned objectives, many algorithms are composed of two (or more) phases. Examples include Gehring and Homberger [15], Bräysy [6], Bent and Hentenryck [3], Bräysy et al. [7], Homberger and Gehring [20], and Lim and Zhang [26]. The first phase attempted to minimize the number of vehicles, and then, the best solution entered the second phase to minimize the total distance. Many different combinations of metaheuristics have been proposed. Gehring and Homberger [15] used an evolution strategy (ES) in the first phase and a TS in the second phase, while Bent and Hentenryck [3] used simulated annealing (SA) and a large neighborhood search. Another idea to fit the lexicographical minimization is using two populations simultaneously. Gambardella et al. [13] developed an ant colony system (MACS-VRPTW) that had two colonies. One colony aimed at minimizing the number of vehicles, and the other colony aimed at minimizing the total distance. Both colonies used independent pheromone trails but shared the global best solution. The first colony attempted to turn an infeasible solution that uses one less vehicle than the global best solution into a feasible solution. Once it found a feasible solution, it restarted after decreasing one more vehicle, and the newly found solution was sent to the other colony to minimize the total distance. A similar concept can be seen in Berger et al. [4], where they proposed a GA that had two populations.

Based on the lexicographical minimization order, the natural way to compare two solutions during the search process is to compare the number of vehicles first and then the total distance if the solutions use the same number of vehicles. However, Homberger and Gehring [19] noted that the minimization of the total distance does not inevitably lead to a reduction in the number of vehicles. (In fact, this arrangement implies that there is a conflict between the two objectives and motivates the use of Pareto approaches in the MOVRPTW.) Thus, they introduced two auxiliary