Optimizing Delivery Time in Multi-Objective Vehicle Routing Problems with Time Windows

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Abstract. The Vehicle Routing Problem with Time Windows involves finding the lowest-cost set of routes to deliver goods to customers, which have service time windows, using a homogeneous fleet of vehicles with limited capacity. In this paper, we propose and analyze the performance of an improved multi-objective evolutionary algorithm, that simultaneously minimizes the number of routes, the total travel distance, and the delivery time. Empirical results indicate that the simultaneous minimization of all three objectives leads the algorithm to find similar or better results than any combination of only two objectives. These results, although not the best in all respects, are better in some aspects than all previously published approaches, and fully multi-objective comparisons show clear improvement over the popular NSGA-II algorithm.

1 Introduction

The Vehicle Routing Problem (VRP) is one of the most important and widely studied combinatorial optimization problems, with many real-world applications in distribution and transportation logistics. It has several variants that take into account different constraints. The variant with Time Windows (VRPTW) is particularly relevant to practical applications, and considers vehicles with limited capacity and specific delivery time windows. Its objective is to obtain the lowest-cost set of routes to deliver demand to customers. Since the problem was originally formulated as a generalization of the Traveling Salesman Problem, cost has primarily been associated with the number of routes and travel distance, but there are several other types of cost.

In particular, companies offering transportation services are often more interested in reducing the overall delivery time (or driver salary cost), than the overall distance traveled (or fuel cost), and there are likely to be trade-offs between them. For the standard VRP, if one assumes a constant vehicle velocity, then counting distances and times are equivalent, but that is not true for the VRPTW because of the time wasted due to arriving before delivery windows. The optimization process needs to produce a set of non-dominated solutions that represent the trade-offs between the objectives, rather than a single solution.

Exact methods can be used to find optimal solutions for small instances of the VRPTW, but the computation time required increases considerably for larger
instances [2]. We are therefore interested in using heuristics to solve this problem, in particular, an Evolutionary Algorithm (EA) that automatically generates a whole population of solutions that cover the full range of trade-offs.

There are many past studies that have solved the VRPTW as a single-objective problem using heuristics. Bräysy and Gendreau [3,4] provide an excellent survey of them, and Bräysy et al. [5] focus on evolutionary approaches.

Other studies have considered the bi-objective optimization of the VRPTW, using an EA to minimize the number of vehicles and the travel distance. Tan et al. [7] used the dominance rank scheme to assign fitness to individuals, and designed a problem-specific crossover operator and multi-mode mutation operator. They also considered three local search heuristics. Ombuki et al. [8] used a Pareto ranking method to assign fitness and proposed further crossover and mutation operators. Finally, our own earlier study [9] incorporated a similarity measure in a Bi-objective Evolutionary Algorithm (BiEA) to select parents for the recombination process in a way that preserved a higher population diversity [10], and that enabled a better set of solutions to be obtained.

The work presented here is an improvement of the BiEA proposed in the last-mentioned study, minimizing not only the number of routes and travel distance, but also the delivery time. We analyze the results and compare them with those from previous algorithms, and introduce improved comparisons with the popular NSGA-II algorithm [6] using fully multi-objective performance metrics.

The remainder of this paper is organized as follows: The next section describes formally the VRPTW, and Section 3 reviews the two multi-objective performance metrics that are used to compare algorithms. Our proposed EA for solving the VRPTW as a multi-objective problem is described in Section 4. Then Section 5 presents the results from our algorithm, as well as comparisons with others already published. Finally, we give our conclusions in Section 6.

2 The VRP with Time Windows

Formally, the VRPTW is defined as a set $\mathcal{V} = \{0, \ldots, N\}$ of vertices. Vertices in subset $\mathcal{V}^* = \mathcal{V} \setminus \{0\} = \{1, \ldots, N\}$ are called customers. Each customer $i \in \mathcal{V}^*$ is geographically located at coordinates $(x_i, y_i)$, has a demand of goods $g_i > 0$, a time window $[b_i, e_i]$ during which it has to be supplied, and a service time $s_i$ is required to unload its goods. The special vertex 0, called the depot, is positioned at $(x_0, y_0)$, has time window $[0, e_0 > \max \{e_i : i \in \mathcal{V}^*\}]$, and demand $g_0 = 0$. It is from the depot that the customers are serviced by a homogeneous fleet of vehicles with capacity $Q \geq \max \{g_i : i \in \mathcal{V}^*\}$. The problem is to design a lowest-cost set of $K$ routes $\mathcal{R} = \{r_1, \ldots, r_K\}$, such that each route begins and ends at the depot, and each customer is serviced by exactly one vehicle.

The travel between vertices $i$ and $j$ has various associated costs, such as the distance $d_{ij}$ and travel time $t_{ij}$. For the standard benchmark problems to be considered later, one assumes unit velocity and direct travel, so the times and distances are both simply taken to be the Euclidean distances. For real-world problems, however, the distances $d_{ij}$ are unlikely to be Euclidean and the travel