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A hybrid multi-objective evolutionary optimization approach for the robust vehicle routing problem☆

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ABSTRACT

In this paper, we propose to approximately solve the robust vehicle routing problem with a population-based method. Uncertainty can be modeled by a set of scenarios where each scenario may represent the travel costs assigned to all visited arcs of the graph associated to the problem. Unlike several existing methods that often aggregate multiple objectives into a compromise function, the goal of the proposed approach is to simultaneously optimize both the number of vehicles to use and the worst total travel cost needed. The proposed method can be viewed as a new version of an evolutionary approach which is reinforced with a "strong-diversification". Such a strategy is based upon destroying and re-building procedures that are hybridized with a local search using a series of move operators. A number of experiments have been conducted to assess the performance of the proposed approach. Its achieved results have been tested on benchmark instances extracted from the literature and compared to those reached by the-state-of-the-art GLPK solver and one of the most recent method available in the literature. The proposed method remains competitive, where encouraging results have been obtained.

1. Introduction

In many real-world applications, some parameters tend to be unknown or uncertain in nature. Making decisions under uncertainty is encountered in numerous domains such as transportation, logistics, telecommunication, reliability and production management. In fact, in some of these cases, most derived problems assume that the parameters are deterministic constants whereas these parameters are generally unknown. Their declared values are very coarse approximations and in such cases, finding a single solution to the problem becomes insufficient. Despite the recent technological progress, tackling several combinatorial optimization problems with uncertainty parameters remains a challenging topic.

The Vehicle Routing Problem (VRP) is a good candidate belonging to the transportation family where uncertainties can often arise on the travel costs linking two customers belonging to a route served by a vehicle. It can also be viewed as one of the most important studied problems in the field of combinatorial optimization, where its objective is to find routes for serving customers with a set of vehicles with limited capacity. These routes start from the depot to serve a number of dispersed customers in a scattered area, then return to the depot. Furthermore, each customer is visited once by only one vehicle, and that the accumulated loads in each route does not exceed the vehicle capacity. Whenever the travel costs between each couple of customers is considered as random, then each travel cost can be characterized by a set of discrete values. Differently stated, one tries to determine a "good" final solution that satisfies all scenarios or the most of the scenarios considered. The resulting problem is known as the Robust VRP (RVRP) (cf. Solano et al. [22]).

Herein, the travel time is represented by a set of scenarios, where each scenario denotes a potential value of the travel time required by a vehicle for following a route. A solution is said to be robust, if it is qualified according to a given robust criterion. Note that, a robust criterion is often represented by an objective function and searching for the best solution according to a robust criterion is equivalent to achieve the best solution optimizing the objective function related to the robust criterion. The robust criteria elaborated in the literature are generally based on the preferential unit risk. Furthermore, other robust criteria have been considered in the literature, like the best case criterion, the worst case criterion (cf., Solano-Charris et al. [22]) and the min-max deviation criterion (cf., Aissi et al. [11]).

Because of the presence of multiple objectives, the expected result for such optimization problems is often a set of optimal solutions that are known as the set of Pareto optimal solutions. Many

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solution methods are available in the literature for tackling multiple objective problems. Among these solution methods, they can be classified into two main categories: Pareto methods and numerical methods. A Pareto method compares two solutions according to the concept of the non-dominated solutions whereas a numerical method is based upon the aggregation principle, like weighted linear aggregation. Differently stated, the first method evaluates the solutions and compare their qualities according to the principle of the non-dominance while the second method tries to build a single objective function and solves the resulting problem as a mono-objective optimization problem. The Non-dominated Sorting Genetic Algorithm-II (NSGA-II) (cf. Deb et al. [7]) tries to mimic the Pareto method, which (i) applies the priority of non-dominated solutions with greater evaluation (fitness) and (ii) assigns the non-dominated solutions to different fronts. In this case, the aim of the non-dominated fronts is to classify the set of solutions according to their ranks and so, to create the diversity in the Pareto solutions.

This paper proposes an evolutionary multi-objective optimization-based approach for tackling the vehicle routing problem with uncertain travel cost (RVRP). The proposed method can be viewed as an extended version of the approach presented in Bederina and Hifi [3], where the non-dominated sorting genetic algorithm-II combined with destroying and rebuilding strategies are employed and hybridized with a local search procedure for trying to enhance the quality of the solutions.

The remainder of the paper is organized as follows. The literature review on the vehicle routing problem and some of its variants is given in Section 2. The presentation and the model used for the problem is described in Section 3.1; that is a model on min-max VRP. Section 3.3 summarizes the non-dominated sorting genetic algorithm-II and the adaptation proposed for the robust VRP. In Section 3.5, the local strategies based operators are described, which are used in order to intensify the search process. The performance of the proposed method is evaluated in Section 5, where its obtained results are argued and compared to those reached by recent algorithms available in the literature. Finally, Section 6 summarizes the contribution of the paper.

2. Related work

The VRP is one of the most important combinatorial optimization problems. It was first proposed by Dantzig and Ramser [6] under the name "track dispatching problem". Given a set of customers with known demands, VRP tries to determine routes with minimum total cost starting and ending at the depot, where a number of identical vehicles with fixed capacity is used. It can be encountered in numerous applications including distribution management, scheduling, transportation, communications, network design and logistics. Depending on different needs and different fields, many variants of the VRP were studied in the literature. These variants either introduce new constraints or modify some assumptions on the basic VRP problem. Among these variants: multiple depots, multi-period horizons, with split delivery and other versions have been tackled (a survey on the VRP and its variants may be found in Kumar and Panneerselvam [13]).

As the exact algorithms are still limited to small-sized instances, heuristics and metaheuristics seems to be a good candidate. Metaheuristics can be considered as one of the most used approaches for solving all types of VRP problem. From 1990's to 2000's, the tabu search was proven in Laporte et al. [15] to be the most successful method compared to some classical heuristics like the Clarke and Wright savings developed in Clarke and Wright [5] and an intuitive procedure proposed by Gillett and Miller [10], where it solved medium-sized instances to optimality (or near-optimality).

During the last decade, evolutionary algorithms were intensively used for tackling the VRP. For instance, the genetic algorithm is one of the evolutionary algorithms that was successfully implemented and tested either for VRP or RVRP. Among the best implementations of such an approach are those proposed by Prins [20] and Baker and Ayechew [1]. A simulated annealing has been also investigated for tackling a hybrid VRP (cf. Yua et al. [24]). Due to the slowness of evolutionary algorithms, they are generally combined with some local moves (hybrid evolutionary algorithms) in order to accelerate the convergence towards local or global optima.

Furthermore, the existing approaches for the VRP often aggregate several objectives and constraints. The aggregation usually does not optimize all the existing objectives at the same time, therefore an objective may be less considered than another one. In some cases, the multi-objective optimization seems to be more effective, because all objectives are simultaneously optimized, therefore no objective is favored over another.

In Jozefowiez et al. [12], the authors proposed a multi-objective variant of the basic VRP problem by optimizing the travel cost and the route balance. The majority of multi-objective approaches available in the literature solve the VRP with time windows variant. Some of them optimizes the travel cost and the number of vehicles simultaneously, like the method proposed in Tan et al. [23], where a hybrid multi-objective evolutionary algorithm was developed, Ombuki et al.'s [19] genetic algorithm with Pareto ranking, Ghoseiri et al.'s [9] genetic algorithm with goal programming, Nahum et al.'s [18] artificial bee colony algorithm and Minocha et al.'s [16] multi-objective hybrid genetic algorithm.

Beside optimizing the number of vehicles and the travel cost, Gacia et al. [8] optimized the total delivery time using a MOEA in addition to similarity measurement and Kumar et al. [14] considered the route balance using fitness aggregated GA.

In other works, a variety of multi-objective optimization problems have been tackled in the literature. The dynamic flexible job shop problem has been studied in Shen and Yao [21], the multi-objective VRP with time windows, by optimizing the travel cost, has been studied in Müller [17] and, the workload imbalance was used in Baños et al. [2], where the multiple temperature Pareto simulated annealing was considered. Finally, the multi-objective VRP with uncertainty was studied in Jozefowiez et al. [12], where both travel cost and route balance were optimized.

3. Tackling the robust vehicle routing problem

3.1. VRP problem formulation

Let $G=(V, E)$ be a complete graph, where V represents a set of n nodes, node 0 represents the depot and the other nodes i, $i \in N=\{1, \ldots, n\}$, represent the customers. Each customer $i \in N$ is characterized by a quantity c_i of goods/demands to be delivered, there are at most m identical vehicles with a capacity C and E denotes a set of arcs with non-negative travel time t_{ij}. The goal of the VRP is to determine a list of feasible routings serving all customers with a *minimum travel distance* and by using a *minimum number of vehicles*. In what follows, $D(.)$ is used for representing the travel cost of a route R or the total travel cost of a list of routes LR. In this case, the travel cost $D(LR)$ is equivalent to the first objective. Formally, the VRP can be stated as follows (cf., Toth and Vigo [20]):

ILP_{vrp}:

$$\min \quad \left(\sum_{\forall R \in LR} D(R), m \right)$$

$$\text{s.t.} \quad \sum_{i=1}^{n} x_{0i} = \sum_{i=1}^{n} x_{i0} \leq m \tag{1}$$