



On solving periodic re-optimization dynamic vehicle routing problems



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ABSTRACT

The Vehicle Routing Problem (VRP) is a complex and high-level set of routing problems. One of its important variants is the Dynamic Vehicle Routing Problem (DVRP) in which not all customers are known in advance, but are revealed as the system progresses. DVRP is a Dynamic Optimization Problem (DOP) that has become a challenging research topic in the past two decades. In DOPs, at least one part of the problem changes as time passes. For DVRP, customers change as a system progresses. Consequently, DVRP applications are seen to operate on a dynamic basis in various real-life systems. To date, a time-based evaluation approach has been used to evaluate periodic re-optimized DVRP systems, which are evaluated by solving while using a specific time budget. In this paper, we solve DVRP while using an enhanced Genetic Algorithm (GA) that tries to increase both diversity and the capability to escape from local optima. Also, we propose a fair weighted fitness evaluation approach as an alternative for the biased time-based approach, regardless of the specifications and power of the running system. The proposed enhanced GA outperformed the previously published algorithms based on both the time-based and weighted fitness evaluation approaches.

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1. Introduction

In the last few decades, our lives have been greatly improved due to advances in transportation and logistics. Transportation and logistics constitute a significant percentage of the total cost of any product. In fact, a company usually spends more than 20% of a product's value on transportation and logistics [1]. Indeed, the transportation system is a sector worthy of consideration, as its size as well as its impact on society continue to increase daily. Nevertheless, it also produces negative impacts, e.g., noise, pollution and/or accidents [2]. However, efficient automated vehicle routing systems with computerized optimization tools could help in minimizing those negative impacts, as well as costs. This is because reduction in distances improves the efficiency of both drivers and vehicles. In addition, these systems could improve customer service, reduce carbon emissions, and decrease administrative costs [1–3]. As a result, the study of routing problems, which are complex problems and relate to real-life systems, has increased tremendously during the last few decades [1,4].

One of the most common and simplest routing problems is the Travelling Salesman Problem (TSP): given a set of cities and distances between each pair of cities, a salesman must visit each city once and return to the starting city throughout the shortest possible route [1,5]. The basic VRP, on the other hand, involves determining an efficient set of multiple TSP routes for a fleet of vehicles that all start and end at a central depot to serve a given set of customers, when each customer should be visited once by only one vehicle. Also, because a single route may exceed an allowed length and/or travel time, there might be a need for multiple routes [2,6,7]. Therefore, the VRP is actually considered to be a more complex, higher-level and broader class of routing problem. A VRP is composed of several variants, such as Capacitated VRP (CVRP), Multi-Depot VRP (MDVRP) and VRP with time windows (VRPTW) [5,8–11]. One of its variants is the Dynamic VRP (DVRP), in which not all the customers are known in advance but instead revealed as time passes [12]. DVRP is considered a Dynamic Optimization Problem (DOP) that has become a challenging research topic over the last two decades. In DOPs, at least one part of the problem changes over time. For DVRP, customers change as the system progresses. Consequently, DVRP applications are seen in various real-life systems that operate on a dynamic basis, e.g., feeder, courier, transport of disabled people and medical emergency services [13]. Like the classic VRP, the DVRP is an NP-hard optimization problem, so optimization techniques that have the capability to produce not exact but high quality solutions under time limitations are the most

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suitable and applicable methods to solve dynamic and deterministic periodic re-optimization DVRP. These optimization techniques include metaheuristics, for example Ant Colony System (ACS) and Genetic Algorithm (GA) [12,14–16].

This paper has two main contributions. The first contribution is solving DVRPs by using an enhanced GA that tries to increase both its diversity and the capability to escape from local optima to find better results. To enhance the GA, five modifications are proposed: the initial population of the first time slice, the initial population of other time slices, the selection process, the swap mutation and the detection/management of the Local Optimal Condition (LOC). A GA is used because one of the best found results, in dynamic and deterministic periodic re-optimization, is that presented by Hanshar and Ombuki-Berman's GA [15]. Generally, this paper only considers minimization problems.

The second contribution of this paper is to propose a new and fairer evaluation approach for DVRP systems. To date a time-based evaluation approach has been used in evaluating dynamic and deterministic periodic re-optimization DVRP systems. In the time-based approach, a DVRP system is run over a specific amount of time for each time slice to solve the problem. However, this evaluation approach is biased; it is based on the specifications and power of the running system. Therefore, four evaluation approaches: generations, raw fitness, weighted fitness and distance calculations are tested as alternatives to the biased time-based approach.

The remainder of this paper is organized as follows. In Section 2, we review DOPs and solution approaches in general. In Section 3, we define the DVRP model handled in this paper and its parameters. In Section 4, we discuss the enhanced GA-based System for DVRP in detail. The experimental methodology, as well as the provided experimental findings, are discussed in Section 5. In Section 6, we discuss a new proposed evaluation approach and then provide the related experimental results and analysis. We conclude by discussing the implications of our results and offering suggestions for the expected future work in Section 7.

2. Dynamic optimization problems (DOPs)

In Dynamic Optimization Problems (DOPs), at least one portion of the optimization problem changes as time passes. These changes may affect the objective function(s) and/or the constraint(s) [17]. These problems have attracted a lot of research effort during the last two decades as many real-world problems change over time, e.g., transportation systems. This section briefly reviews some of the most typical approaches that have been proposed to solve Dynamic Optimization Problems (DOPs) in general.

2.1. Introducing diversity when changes occur

In this category, methods try to introduce diversity into their population when a change is detected, e.g., by adding randomised individuals. These methods are good at solving dynamic problems with continuous changes, and when the changes are small and medium [18]. However, these methods might have some disadvantages, for example, they suggest that the changes are easy to detect [18].

2.2. Maintaining diversity during the search

In this category, methods try to maintain diversity in the population during solving the problem, e.g., by explicitly keeping individuals from getting close to one another [19]. These methods are good at solving dynamic problems with both large and slow changes [20]. However, these methods might suffer from some disadvantages, e.g., focusing on diversity may retard, or even misguide the search process [17].

This category is the closest to that used in this paper, as this approach aims to increase both its diversity and the capability to escape from local optima. To do this, some modifications have been proposed to maintain diversity, e.g., the selection process, the swap mutation and the detection/management of the Local Optimal Condition (LOC).

2.3. Prediction approaches

In this category, it might be helpful that methods try to learn patterns from previous search periods, and to then use that knowledge to try to predict changes in the future. These methods are used when changes have regular patterns [21]. One of the common prediction approaches is to predict the characteristics of moving optima. These approaches may become very effective if the predictions are accurate, so the algorithms could detect/track/find the global optima quickly [18]. However, these methods also have some disadvantages, e.g., training errors.

2.4. Multi-population approaches

In this category, methods consist of multiple sub-populations concurrently [18,21]. These methods have multiple advantages such as they could maintain enough diversity to adaptively start a new search whenever a new change appears [21]. However, these methods also have some disadvantages, e.g., too many sub-populations may slow down the search process [18].

We refer the reader to the surveys [21] and [17] for more details and more critiques of DOP solution approaches.

3. Dynamic vehicle routing problem (DVRP)

In this paper, we investigate a DVRP model similar to the one that was first introduced by Kilby et al. [22], and which has been further refined by Montemanni et al. [14]. This model is considered a dynamic and deterministic periodic re-optimization routing problem [12,13]. Montemanni et al. [14] considered DVRP as an extension to the standard VRPs that are created by decomposing a DVRP into a sequence of static VRPs. Like the static VRP, DVRP aims to minimize the overall cost of each solution that uses m vehicles under the following constraints:

- each vehicle starts from and returns to the same depot;
- each customer is served once by only one vehicle; and
- each vehicle has a limited carrying capacity, Q , for a commodity. Customers' demands that a vehicle would serve along any route assigned to it must not exceed Q .

The main difference between the static and dynamic VRPs is that in the latter, new orders arrive after the working day has already started, so it is necessary to dynamically change the optimization search process [14]. In a periodic re-optimization model, a DVRP is modelled as a sequence of static VRP instances which contain all the customers known at each particular time, but who are not yet served [13]. DVRP has a parameter, degree of dynamism (dod), which is the ratio of the known to unknown customers when the system starts [13]:

$$dod = \frac{\text{count of customers (known in advance)}}{\text{all customers}} \quad (1)$$

where $dod \in [0,1]$. If dod is 1, all requests are known in advance (completely static problem), while if it is 0, no requests are known in advance (completely dynamic problem).

As well as the basic VRP data, the DVRP has the following three types of data [14,22]:

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