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A memetic approach to vehicle routing problem with dynamic requests

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ABSTRACT

The paper presents an effective algorithm for solving Vehicle Routing Problem with Dynamic Requests based on memetic algorithms. The proposed method is applied to a widely-used set of 21 benchmark problems yielding 14 new best-know results when using the same numbers of fitness function evaluations as the comparative methods. Apart from encouraging numerical outcomes, the main contribution of the paper is investigation into the importance of the so-called *starting delay* parameter, whose appropriate selection has a crucial impact on the quality of results. Another key factor in accomplishing high quality results is attributed to the proposed effective mechanism of knowledge transfer between partial solutions developed in consecutive time slices. While particular problem encoding and memetic local optimization scheme were already presented in the literature, the novelty of this work lies in their innovative combination into one synergetic system as well as their application to a different problem than in the original works.

1. Introduction

Vehicle Routing Problem (VRP), first introduced by Dantzig and Ramser in [1], is an NP-hard combinatorial optimization problem with many practical applications. In its classical formulation a set of customers must be served by a fleet of homogenous vehicles (with some pre-defined capacity) with routes beginning and ending at a specified depot. The optimization goal is to minimize the total routes' length/cost of all vehicles. Due to the VRP's combinatorial complexity the exact solution methods proved inefficient, except for simple problems. Therefore most of the research effort was devoted to application of metaheuristic algorithms, for instance Ant Colony Optimization (ACO) [2], Tabu Search (TS) [3], Genetic Algorithms (GA) [4], Simulated Annealing (SA) [5] or Upper Confidence Bounds Applied to Trees (UCT) [6], with promising results.

In majority of practical applications, however, another dimension related to stochastic nature of the real-life problems is added to the problem's formulation. In particular, the information available at the beginning may change during the solution execution, for instance due to the arrival of new customers' orders [7,8] or because of the changes in their requested demands [9] or because of unplanned events, e.g. traffic jams/road congestion [10,11] or, more generally, due to stochastic travel times [12]. This intrinsic stochasticity of the practical VRP realizations led to the extension of the static VRP to a class of Dynamic Vehicle Routing Problems (DVRP), solving which requires adequate on-line routes' adjustment in response to the arrival of new problem-related information.

Furthermore, in the literature there are many variants of the VRP which are formulated so as to serve specific practical needs, e.g. its multi-trip [13] or multi-compartment [14] versions, variants with specific time-windows for delivery [15], formulations which combine delivery with picking up goods from the clients [16], and many others (see the recent special issue [17] for an overview of the current developments and challenges in this domain and [18] for the VRP taxonomy).

This paper considers a version of DVRP in which some of the customers' locations (and their associated requests) are unknown at the start of the solving method and arrive gradually as time passes, i.e. during the algorithm execution. In the literature, this version of DVRP is known as Vehicle Routing Problem with Dynamic Requests (VRPDR). The intrinsic partial information uncertainty of VRPDR is usually handled in the way proposed by Kilby et al. [8], which consists in executing the route optimization procedure only at the end of pre-defined fixed time intervals – called *time slices*.

In general, the algorithms applied to solving VRPDR are similar to those used for VRP. In particular, Computational Intelligence methods, e.g. ACO [19], TS [20], GA [20] or PSO [21,22], have been

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applied to the problem with some success. Specifically, the PSO based approaches [23,24,22,25], seem to be very well suited to the type of dynamic changes introduced to requests' distribution observed in VRPDR. This issue is further discussed in Section 5 devoted to presentation of experimental results.

The approach proposed in this paper is based on Memetic Computing (MC) [26,27], which is currently one of the fastest growing subfields of Evolutionary Computation research. In short, MC enhances population-based Evolutionary Algorithms (EA) by means of adding a distinctive local optimization phase. The underpinning idea of MC is to use domain knowledge or local optimization techniques to improve potential solutions (represented by individuals in a population) between consecutive EA generations. A synergetic combination of simple local improvement schemes called *memes* with evolutionary operators leads to complex and powerful solving paradigm, applicable to a wide range of problems [28].

MC has been applied to several variants of transportation problems, in particular the static VRP version [29,30] or the Vehicle Routing Problem with Stochastic Demands (VRPSD) [9]. However, to the best of our knowledge, this paper presents the first attempt to solving VRPDR with MC. On the other hand our approach, to some extent, follows the above-cited work of Chen et al., even though the problems considered in these two papers are quite different. In VRPSD, unlike in VRPDR, all customers' locations are known in advance (at the start of the method) but customers' demands are stochastic, i.e. the size of demand is known only after the vehicle's arrival. Hence, the main focus of the solution method is to ensure that a planned route would not exceed vehicle's capacity.

Another paper that inspired our work is [20] where simple but powerful chromosome representation and genetic operators were proposed. While a unique combination of the MC scheme adopted from [9] with solution representation proposed in [20] proved to be superior over each of the two components alone, the respective results were, anyway, not better than those accomplished with the 2MPSO (Two-Phase Multiswarm PSO) method [22,25]. Only after the proposed method was enhanced by a suitable *starting delay* mechanism and the effective way of *knowledge transfer between consecutive time slices*, the final results yielded by the system excelled those of 2MPSO in terms of the average performance and the best minima found.

The main contribution of this paper, except for finding new best-literature results for popular benchmarks is investigation into the saliency of the *starting delay* parameter. Another key issues are introduction of a new effective way of knowledge transfer between consecutive time slices by means of a specific population generation scheme, as well as, introduction of a new mutation operator in the memetic optimization procedure. The novelty of this work also lies in the innovative synergetic combination of (already known in the literature) problem encoding and memetic optimization and their application to a new problem from VRP domain.

The remainder of this paper is arranged as follows. Section 2 presents the VRPDR definition and discusses its practical relevance. In Section 3 general overview of the system's construction, its main principles, as well as basic components (each in a dedicated subsection) are presented. Section 4 provides benchmarks description, discussion on experimental methodology and parameters' selection. In Section 5 experimental results are presented and discussed in the context of the best literature solutions, in particular those accomplished with the 2MPSO algorithm [21,22,25]. Performance analysis of the proposed system and discussion on its suitability for particular types of benchmark sets are also placed in this section. The next section elaborates on the pertinence of the local memetic optimization component and the saliency of the method's steering parameters. The last section is devoted to conclusions and directions for future research.

2. Definition of VRPDR

VRPDR is a generalization of the Traveling Salesman Problem. In this problem a fleet of m homogenous vehicles, each with identical capacity c, and the set of n customers $\{v_1, v_2, \ldots, v_n\}$ are considered. VRPDR can be modeled using an undirected graph $G = (V, E)$, where $V = \{v_0, v_1, \ldots, v_n\}$ is the vertex set and $E = \{(v_i, v_j) : v_i, v_j \in V, i < j\}$ is the edge set. Each vertex $v_i, i = 1, \ldots, n$ represents the respective (ith) customer and v_0 denotes a depot. Each edge $e_{ij} = (v_i, v_j), i, j = 0, \ldots, n, i \neq j$ has an associated weight which represents the cost or, alternatively, a distance between v_i and v_j being either two customers or a customer and the depot. Furthermore, for each customer v_i the demand d_i, the unload time ut_i (which is the time required to unload cargo at customer's v_i) and t_{v_i} – the time of arrival of the order from customer v_i, are defined. Depot v_0 has the opening time t_o and the closing time t_c, $(0 \leq t_o < t_c)$ specified. The speed of each vehicle is defined as one distance unit per one time unit.

The goal of VRPDR is to minimize the total routes' length of all vehicles according to the following constraints:

- each vehicle has to start from a depot after time t_o and end its route in a depot before time t_c,
- every customer has to be served exactly once and by one vehicle,
- time of a vehicle's arrival to customer v_i has to be greater than t_{v_i} for all i,
- the sum of customers' demands assigned to each vehicle must not exceed vehicle's capacity c.

VRPDR combines two NP-Complete problems: Bin Packing Problem (to assign requests to vehicles) and Traveling Salesman Problem (to minimize the tour length of each vehicle). The problem is widely applicable to real-life tasks, such as taxi services, courier companies or other pickup and delivery businesses. The Global Positioning System and the widespread use of mobile phones create opportunity for companies to track and manage their fleet in real time, thus making the VRPDR a highly relevant problem of practical importance.

3. Components of the system

Our system designed to solving the VRPDR is composed of two main components. The first module is responsible for receiving new orders, dividing working day into some pre-defined number of time slices and creating static instances of the VRP for each of them. The second component is responsible for optimizing the routes by means of solving a (static) VRP instance in each time slice. To this end a GA implementation following Ombuki-Berman et al. paper [20], enhanced with the local memetic optimization [9] is proposed.

3.1. Time slices

Following [8] and many other subsequent papers, a working day is split into n_{ts} equal-length time slices and in each time slice a static version of the problem (VRP) is solved for the set of currently known customers (requests). New requests arriving during the current time slice are postponed to its end and optimized in the next algorithm's run (in the next time slice).

Once the calculations allotted for a given time slice are completed the best-fitted chromosome is selected, decoded and the vehicle routes it represents are examined. Roughly speaking, if the time-span of a planned route allows for a "safe time reserve" the vehicle is not moving as it is generally beneficial to wait for another time slice and include newly-arrived requests in the planned solution. Certainly, waiting for too long poses the risk of not being able