A Simulated Annealing Hyper-heuristic: Adaptive Heuristic Selection for Different Vehicle Routing Problems

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1 Introduction

One of the motivations of hyper-heuristic research is to investigate the development of adaptive decision support systems that can be applied to a range of different problems and different problem instances [5]. One possible approach is to dynamically adjust the preferences of a set of simple low-level heuristics (or neighbourhood operators) during the search. Hyper-heuristics have been used to address a variety of search problems, including educational timetabling [6, 2, 8, 7], scheduling [10], and packing and layout optimisation [1, 9]. In this research, we intend to further investigate an adaptation mechanism in the context of vehicle routing problems (VRP).

VRP has numerous practical applications and it has been one of the most studied combinatorial optimisation problems in the past fifty years. Several variants of VRP have been addressed. Examples include capacitated VRP, VRP with time windows, multiple depot VRP, periodic VRP, stochastic VRP, and VRP with pickup and delivery. However, most existing algorithms for these problems are tailored for a particular problem variant and it is generally difficult to reuse the same algorithm for a different scenario without significant algorithm redevelopment or parameter-tuning. Recently, there are a few important research papers being carried out to improve the generality of algorithmic methods so that they can handle problems across more than one VRP variant [11, 12]. In both papers, the searches are based on combinations of “destruction-repair operators”, guided by some problem dependent penalty functions. In this abstract, we want to continue this research direction using a simulated annealing hyper-heuristic technique in order to investigate how the algorithm can intelligently choose between different neighbourhood operators (heuristics) according to the different problems. In particular, we consider two of the most popular variants of vehicle routing problems (capacitated VRP and VRP with time windows) and investigate the adaptation of the heuristic-selection mechanism across these variants and at different stages of the search. Specifically, we want to investigate: 1). How the hyper-heuristic adapts to these two types of vehicle routing problems by changing preferences of low-level heuristics and whether the hyper-heuristic can automatically identify heuristics that are particularly good for a given type of vehicle routing problem? 2). How the hyper-heuristic adapts its selection decision during different stages of the search when solving a particular problem instance?

2 Vehicle Routing Problems

The Vehicle Routing Problem (VRP) [16] describes a whole class of problems in which a fleet of vehicles (based at one or several depots) must serve geographically dispersed customer demands.

The objective is usually to minimise the total cost, in terms of vehicle fleet size, travelling distance and/or travelling time. The VRP is a well known NP-Hard problem for which no polynomial time algorithm is known.

2.1 The capacitated vehicle routing problem

The capacitated vehicle routing problem (CVRP) is a version of VRP, in which a fleet of m vehicles of the same (limited) capacity Q is available and the objective is to minimise total travel distance. The CVRP can be formulated as a connected graph $G = (V, E)$ of $n + 1$ nodes, with each node $v_i \in V, i = 1, ..., n$ representing a customer of demand q_i and vertex v_0 representing the depot. The problem is thus to find a set of vehicle routes, denoted as $R = \{r_j | j = 1, ..., m\}$, so that every customer is served by exactly one vehicle-visit and the total customer demand on each route r_j does not exceed the vehicle capacity Q [15].

2.2 Vehicle routing with time windows

Vehicle routing with time windows (VRPTW) is an important variant of VRP with many applications [3, 4]. It is very similar to CVRP but, in VRPTW, each customer is associated with a time window, which defines an interval wherein the customer has to be served. The interval at the depot is called the scheduling horizon. If a vehicle arrives at a customer before the time window of that customer, the service cannot start until time reaches the time window.

Note that even VRPTW itself has several variants. In this research, we are concerned with the same model that has been addressed by most researchers. That is, the graph is complete and the edge costs are symmetric. The objective is hierarchical: one first seeks to minimise the size of the fleet required to service customers and, in the second step, the total distance traveled by the fleet. Considering the hyper-heuristic approach used in this research, the solution can be represented by m linked lists, with each linked list $j \in m$ representing one vehicle schedule and each node in j representing a customer to be served by j in the same sequence.

3 Simulated annealing hyper-heuristics

We focus on a recently proposed simulated annealing hyper-heuristic framework [2] which has demonstrated generality across the university course timetabling problem, the nurse rostering problem, and the bin packing problem. The set of low-level heuristics (neighbourhood operators) for both the CVRP and VRPTW is drawn from the literature. These heuristics are briefly described below.

- **Relocate**. This heuristic moves a random customer from its current route to a different one.
- **2-opt* exchange**. This heuristic is specially designed for VRPTW. It is a generalisation of the 2-opt operator for TSP in order to satisfy the time-window constraints. The main modification over 2-opt is that the exchange maintains the direction of the original routes by introducing the customers with late time windows after customers with early time windows [13].
- **k-opt**. This is a very efficient neighbourhood operator for the travelling salesman problem.
- **Or-opt exchange**. This heuristic generally operates on a single route and changes the position of a random sub-route (no more than three customers) within the current route [13].

- **CROSS exchange**. This heuristic is a very effective heuristic for VRPTW. It exchanges two route-segments from two different routes and also preserves the orientation of customers [14].
- **Ejection-Chain**. This heuristic repeatedly moves conflicting customers, triggered by a random customer relocation operation, from their current routes to other ones until the feasibility of the solution is recovered [3].

4 Summary

In summary, we plan to utilise a simulated annealing based hyper-heuristic for two classes of vehicle routing problems (capacitated VRP and VRP with time windows). Our hypothesis is that the hyper-heuristic algorithm will produce good quality solutions across a range of problem instances, without having to resort to tuning parameters for each instance. We will report on the results of these experiments at the conference.

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