Selection and Generation Hyper-heuristics for Solving the Vehicle Routing Problem with Time Windows

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ABSTRACT

The vehicle routing problem is a classic optimization problem with many variants. One of the variants is given by the inclusion of the time windows constraint which requires the clients to be served within a delimited time frame. Because of its complexity, vehicle routing problems are usually solved by using heuristics without optimality guarantee. This paper describes two hyper-heuristics capable of producing results comparable to the ones obtained by the best-performing heuristics on different sets of benchmark instances.

Keywords

Hyper-heuristics; Heuristics; Genetic algorithms; Genetic programming

1. INTRODUCTION

This work explores the benefits of using hyper-heuristics [2] for solving the vehicle routing problem with time windows (VRPTW). Two hyper-heuristic models are proposed, one for generating constructive heuristics and the other for selecting a suitable improvement heuristic, given the properties of the problem at hand.

2. BACKGROUND AND RELATED WORK

A few works have explored the use of hyper-heuristics for solving the VRP. Among them, we can mention the development of some hyper-heuristic approaches for the VRP by using the HyFlex Framework [1]. Garrido and Castro [4] proposed an evolutionary hyper-heuristic approach to solve the dynamic VRP. Also, the work developed by Marshall et al. [5] is relevant to this investigation as they described a grammatical evolutionary-based hyper-heuristic for the capacitated VRP. To the best of the authors' knowledge, the use of hyper-heuristics to solve the VRPTW remains unexplored in the literature.

We have considered two types of heuristics for this investigation: *constructive heuristics* and *improvement heuristics*. A constructive heuristic defines a way to decide the position of the customers in a route and creates new routes as needed until all the clients have been assigned a route. On the other hand, improvement heuristics require an initial solution to work with, as they modify the placement of the customers within the routes. Thus, the role of the improvement heuristics is to reduce the distance required to visit all the clients. The constructive heuristics used in this research are: nearest neighbor (NNH), coefficient weighted distance time (CWTH) and Solomon's sequential insertion (SSI). Conversely, the improvement heuristics analyzed include: intra-route relocate (IRR), inter-route relocate (IERR), inter-route exchange (IERE) and inter-route 2-Opt (2OPT). More information on these heuristics can be consulted at [6] and [3].

3. HYPER-HEURISTIC APPROACHES

We used two evolutionary-based hyper-heuristic models to solve the VRPTW. The first model consists of a generation hyper-heuristic that is based on genetic programming to produce constructive heuristics. These new heuristics combine the features that characterize the customers in the VRPTW to rank them and decide the next one to assign to a route –it constructs a solution by adding one customer at a time. The second model, a selection hyper-heuristic, uses a genetic algorithm to produce rules that decide when to apply a particular improvement heuristic to increase the quality of already feasible solutions. This model produces rules that indicate when one specific improvement heuristic should be used.

4. EXPERIMENTS AND RESULTS

56 instances taken from the literature [6] were divided into six types: R1, R2, C1, C2, RC1 and RC2. Sets R1, C1 and RC1 have a short scheduling horizon which makes the length of the route-time to act as a constraint, allowing only a few customers to be served by the same vehicle. In contrast,

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Table 1: Performance of the constructive heuristics taken from the literature and the best of five constructive heuristics produced with the genetic-programming-based generation hyper-heuristic model (best results are shown in bold).

Method	C1	C2	R1	R2	RC1	RC2
NNH	1672.644	1327.566	1771.148	1944.424	2048.958	2393.524
CWDTH	1688.764	1319.232	1739.774	1940.811	2018.861	2397.524
SSI	1509.756	900.7383	3401.030	2825.945	4354.056	4064.084
HG	**994.0217**	**808.4852**	**1577.802**	**1424.007**	**1867.722**	**1621.735**

Table 2: Performance of the improvement heuristics taken from the literature and the best of five improvement heuristics produced with the genetic-algorithm-based selection hyper-heuristic model (best results are shown in bold).

Method	C1	C2	R1	R2	RC1	RC2
BEST	**1285.412** **(SSI + 2OPT)**	**770.2258** **(SSI + IERE)**	1469.430 (CWDTH + 2OPT)	1207.985 (NNH + IERE)	**1732.083** **(NNH + 2OPT)**	1428.816 (CWDTH + IERR)
NNH + HS	1625.169	1247.522	1692.884	1715.541	1995.574	2192.267
CWDTH + HS	1402.829	851.7727	**1451.488**	**1207.665**	1747.269	**1438.409**
SSI + HS	1332.612	847.3597	1566.078	1296.152	1922.210	1504.247

sets R2, C2 and RC2 have a long scheduling horizon. The former, together with large vehicle capacities, allows many customers to be served by the same vehicle [6].

By using the generation hyper-heuristic model we produced five constructive heuristics that guarantee to produce satisfiable instances. The best among these five heuristics (HG) was used to solve the 56 instances and compared against the results of the constructive heuristics described in Sect. 2. Table 1 depicts the average total distance required by each initial solution produced by the constructive heuristics analyzed in this work for each group of instances.

Later, we used a genetic-algorithm-based selection hyper-heuristic model to produce five heuristic selectors that recommend, at each stage of the search, which improvement heuristic from the ones described in Sect. 2 to apply. Because improvement heuristics require a solution to modify, we used the best heuristic selector (HS) together with each of the constructive heuristics studied in this work to solve all the instances in this investigation and reported the results. Table 2 presents the average total distance required by each improvement method on each particular group of instances.

As the results from Table 1 suggest, the constructive heuristic obtained through the genetic-programming-based hyper-heuristic outperformed the constructive heuristics taken from the literature. When the heuristic selector produced by the selection hyper-heuristic was used to solve the benchmark instances, we observed evidence of synergy with CWDTH. Only when CWDTH was used to construct the initial solution the performance of HS was maximized.

5. CONCLUSION AND FUTURE WORK

In this article, we proposed two hyper-heuristic models to solve the VRPTW. A genetic programming-based generation hyper-heuristic produced a constructive heuristic based on the components of existing heuristics for the problem. Later, a genetic-algorithm-based hyper-heuristic was used to produce a heuristic selector that manages how improvement heuristics are used as the search takes place.

As future work, our interests are two-fold: (1) we want to study the behaviour of the model when new heuristics are incorporated and, (2) we expect to explore the possibilities of hybridization between different types of hyper-heuristic approaches, particularly focusing on a model that produces both heuristics and heuristic selectors.

6. ACKNOWLEDGMENTS

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