A metaheuristic for solving large instances of the School Bus Routing Problem

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1 Introduction

This research is motivated by a real-life school bus routing problem (SBRP). In the Flemish region (Belgium), transport of children to their school is organized by the Flemish transportation company. Each pupil having the right to be transported to its school, also has the right to a bus stop located at a distance less than 750 metres from its residence. To efficiently design the routes, a set of potential stops is determined, so that each pupil has at least one stop he/she can walk to. Routes are then determined for the school buses so that all students are picked up at a stop they are allowed to use, while making sure that the capacity of the buses is not exceeded. Flemish transportation company are faced with problems where up to 3000 students have to be picked up and brought to 7 different schools. The basic SBRP as described in [3] is a generalization of the basic vehicle routing problem (VRP) and therefore also NP-hard. In general, the VRP defines an optimization problem where allocation of stops to vehicles and the optimal sequence of stops with corresponding demands have to be determined without violating vehicle capacities. Different constraints can be envisaged such as maximum distance constraint and time windows. The total distance covered by all vehicles acts as a criterion has to be minimized [4]. In contrast with the basic VRP, total demand for each stop is not known beforehand. We only know whether a student is allowed to walk to a stop or not. This gives us the possibility to incur potential savings (e.g. not have to visit a stop), since we can assign students to stops ourselves. However, introducing these extra assignment decisions makes the problem much more difficult to solve. Figure 1 shows an example of such a SBRP. In this figure, dots represent students, the small squares represent potential stops, the large square
represents the school. Dotted lines indicate which stop a student is allowed to walk to. Assuming that the capacity of the buses is 8, a possible (but not necessarily optimal) solution to this problem is shown also in Figure 1. The figure below makes it clear that buses depart at the school itself and that they do not necessary visit all stops.

Figure 1: Example of (un)solved school bus routing problem

Contrary to the literature on the ordinary VRP and several of its extensions (e.g. time windows), only a limited amount of research has considered the routing of school buses. Moreover, only a very small number of papers treats the simultaneous selection of stops. Most school bus vehicle routing formulations focus on formulating extra constraints and/or objectives to take some student-related factors into account. To the best of our knowledge other (almost) similar problems such as the Multi-Vehicle Covering Tour Problem [1] or the Capacitated m-Ring Star Problem [2] do not simultaneously take into account the vehicle capacity and the student-stop restrictions. The focus of this paper is not on building such intricate multi-objective models of similar problems, but on understanding the problem in its simple form, i.e. uncovering the relationship between assignment and routing decisions and building a powerful meta-heuristic to solve large instances quickly. In order to reach these goals, we restrict ourselves in this paper to a single school, one type of student and one type of bus, with fixed capacity.

2 Solution Method

For VRPs there exist a myriad of solution techniques (exact algorithms, heuristics, metaheuristics). In [3] experimental results on medium-sized instances (10 stops, 50 students) it was shown that for exact methods a large variability in computation time already exists ranging from 2 minutes to even more than 64 hours. One may argue that SBRPs are typical tactical problems for which computational performance is not a big issue, but managers/decision makers want to have the opportunity to quickly assess solutions for different scenarios. Moreover, next to the obvious school bus routing application, this problem formulation has other applications (e.g. parcel delivery service) where more than in a school bus routing context fast running times are required. Therefore, for large instances as we encounter in practice (50 stops, 500 students per school) probably only metaheuristics such as Tabu Search (TS), Variable Neighbourhood Search (VNS). . . could be applied effectively. Our solution method starts with a GRASP-like savings algorithm (construction phase), after which a VNS algorithm (improvement phase) is used to improve the initial solution. The construction phase begins with a solution where all stops are visited directly. After this initial setup, students are assigned to these stops solving a modified version of the transportation problem.

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Obviously, if no feasible assignment could be returned, no feasible solution for our SBRP exists. On the opposite, if the algorithm returns a feasible solution then we can proceed with a savings heuristic where step-by-step a new solution is build by combining routes. While normally we would be tempted to choose the move with the largest saving, selection is now randomized in order to diversify the search. Randomization when selecting a move is introduced in two manners, more specifically regular and roulette randomization. When roulette randomization is applied moves with larger potential savings have relatively more chance to be selected than moves with lower savings. For the VNS improvement phase, several typical neighbourhoods are defined by the following moves: changing stops within a route, changing stops between two routes and replacing stops from one route to another. Only when vehicle capacity is violated by a move mentioned above, students are re-assigned to the visited stops of the proposed solution. In addition, a specific move for this problem was implemented which removes one visited stop from a route and adds the best possible unvisited stop back into our solution.

3 Experimental Results

Experimental results indicate that our method performs very well on medium-sized instances for which exact algorithms already show variable performance. In contrast, our meta-heuristic approach produces near-optimal solutions (Table 1) within a time span of a couple of seconds for these medium-sized instances (Table 2). Finally, results on much larger instances will be reported.

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Table 1: Comparison quality to bounds in %

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Table 2: Solution speed (s)

References


