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# An adaptive large neighborhood search heuristic for the Electric Vehicle Scheduling Problem

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ABSTRACT

This paper addresses the Electric Vehicle Scheduling Problem (E-VSP), in which a set of timetabled bus trips, each starting from and ending at specific locations and at specific times, should be carried out by a set of electric buses or vehicles based at a number of depots with limited driving ranges. The electric vehicles are allowed to be recharged fully or partially at any of the given recharging stations. The objective is to firstly minimize the number of vehicles needed to cover all the timetabled trips, and secondly to minimize the total traveling distance, which is equivalent to minimizing the total deadheading distance. A mixed integer programming formulation as well as an Adaptive Large Neighborhood Search (ALNS) heuristic for the E-VSP are presented. ALNS is tested on newly generated E-VSP benchmark instances. Result shows that the proposed heuristic can provide good solutions to large E-VSP instances and optimal or near-optimal solutions to small E-VSP instances.



## 1. Introduction

In recent years, a growing public concern about greenhouse gas emissions and health related pollution from the transportation sector has led to more attention to electric and other alternative fueled vehicles both in academies and industry [23]. Large vehicles such as buses contribute largely to this issue. For instance, in Copenhagen, Denmark, buses travel approximately 110 million kilometers a year and the bus fleet on average produces around 0.9 kg $CO_2$ per kilometer along with other pollutants [17]. Moreover, buses operate mainly in urban areas with dense population and therefore cause the greatest impact on health. If the public transit switched to zero-emission electric buses, the pollution in the city could be reduced significantly.

However, it is not trivial to substitute conventional buses with electric buses due to existing disadvantages of battery driven vehicles, e.g., limited battery capacity and long recharging time. These limitations result in 'range anxiety', which is the fear of running out of battery and the concern of making an unplanned trip [2].

On the other hand, within commercial transport, a high degree of planning could be expected especially in the schedule based transportation sector, which carries out schedules with high punctuality according to a timetable. This suggests that electric vehicles have a good potential to be used for urban bus operations. However, to better utilize electric buses, the above-mentioned limitations must be taken into consideration during planning. This is the motivation of studying the Electric Vehicle Scheduling Problem (E-VSP) in this work.

The E-VSP, in which a set of timetabled trips should be assigned to a set of electric vehicles with limited driving ranges based at different depots, is an extension of the well-known Vehicle Scheduling Problem (VSP). The E-VSP can be described as a Multi-Depot VSP with distance constraints and charging possibilities. In the E-VSP, each trip starts from and ends at specific locations at predefined times. Each vehicle can be recharged fully or partially at any given recharging station. The recharging time is assumed to be a linear function of the amount of charged battery.

An E-VSP solution is a set of vehicle schedules, where each vehicle starts from and ends at its base depot, each trip is covered by exactly one vehicle and the vehicles' driving ranges are not exceeded. The objective is to first minimize the number of vehicles used and secondly minimize the total distance traveled. As the traveling distance of each trip is fixed, minimizing the total traveling distance is equivalent to minimizing the distance between the depot and the trip and between any two trips in the schedule, also known as deadheading distance.

The VSP has been extensively studied in the literature and

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extended to different variants, including the Multi-Depot VSP (MD-VSP) [4,6], the Multiple Vehicle Types VSP [16], and the VSP with Route Constraints (VSP-RC) [5] where different types of route constraints can be enforced, including route duration [11], route distance [4] or maximum vehicle bus line changes [15]. All the above-mentioned VSP variants consider conventional vehicles and none of them allows recharging. A variant of the VSP that considers recharging/refueling options is the Alternative Fuel Vehicle Scheduling Problem (AF-VSP) studied by Adler [1]. In his problem, the alternative fuel vehicles are allowed to be refueled at given recharging stations to prolong the total distance the vehicles can travel. However, the AF-VSP is different from our E-VSP in the following aspects: (1) the AF-VSP only considers full charging. The vehicle's fuel level is set to full after visiting any recharging station; whereas the E-VSP considers partial charging, and introduces an extra decision on the necessary charging amount for each visit at any recharging station; (2) the charging time in the AF-VSP is fixed regardless of the remaining fuel level; whereas our charging time is assumed to be a linear function of the charged amount. In other words, the AF-VSP is a special case of our E-VSP. In Adler [1], the author proposes a construction heuristic as well as a column generation approach to solve the AF-VSP, and tests his algorithms on the metropolitan bus system of Phoenix, Arizona.

Another thread of literature relevant to the E-VSP is the Vehicle Routing Problem (VRP) for electric/alternative fuel vehicles, where the vehicles are used to serve a set of customers instead of the timetabled trips. Erdoğan and Miller- Hooks [9] introduce the Green Vehicle Routing (G-VRP). Similar to Adler [1], they also assume full charging and a fixed charging time for each visit to the recharging station. Felipe et al. [10] consider an extension of the G-VRP, where recharging stations are of different types with different costs and recharging speeds. Moreover, partial charging is allowed and the recharging time is assumed to be a linear function of the amount of energy recharged. Schneider et al. [21] extend the G-VRP to the Electric Vehicle Routing Problem with Time Windows (E-VRPTW) by considering customers' time windows, unlimited number of recharges per route and a variable recharging time which depends on the remaining fuel level when a vehicle arrives at the recharging station. However, partial charging is still not an option in Schneider et al. [21], i.e., a vehicle must be fully recharged when leaving the recharging station. Hiermann et al. [14] study the Electric Fleet Size and Mix VRPTW, where electric vehicles with different battery capacities, load capacities, energy consumptions and recharging rates are used. In Goeke and Schneider [12] a mixed fleet of electric vehicles and conventional vehicles is used. Desaulniers et al. [7] further extend the E-VRPTW by allowing partial charging. They develop branch-price-and-cut-algorithms to solve different variants of the problem with single/multiple-recharge and full/partial-recharge. They test their algorithms on benchmark instances and demonstrate the benefit of multiple-recharge and partial-recharge.

In this work, we consider the electric scheduling problem with partial recharging described in Section 2, and present a mathematical model (Section 3) as well as an Adaptive Large Neighborhood heuristic (Section 4) for solving this problem. The heuristic is tested on newly generated E-VSP instances. Computational results are provided in Section 5, followed by a conclusion and future work in Section 6.

## 2. Problem description

The input to the E-VSP includes a set of timetabled trips, a set of vehicles, a set of depots and a set of recharging stations. Each trip has a specific start time, end time, start location, end location and traveling distance. Each vehicle has a limited driving range, and should start from and end at its base depot. The vehicle's fuel consumption is assumed to be a linear function of the traveling distance. The consumption rate, i.e., the amount of fuel consumed per unit distance, is given. The vehicles can visit any recharging station to recharge any amount up to the full battery capacity. The charging time is assumed to be a linear function of the battery charge gained and the charging rate, i.e., the time needed for charging one unit battery, is also given. The distance and the time for the deadheading traveling between any two timetabled trips and between any depot/station and any timetabled trip are known. The problem is to find a set of least-cost schedules for the vehicles to perform the timetabled trips. Each trip should be covered by exactly one schedule that is performed by one vehicle. The charge level of the vehicle must be non-negative at any time throughout the schedule. The cost consists of a relatively high pullout cost of using each vehicle and an operational traveling cost.

To illustrate this problem, a small example consisting of two timetabled trips, one recharging station and one depot is given in Fig. 1. The start time, end time, start location and end location of the trips are given in Table 1. The travel time and the distance of each arc are assumed to be the same, and are given in the figure. The vehicle range is 30. Both the consumption rate and the charging rate are 1. The pullout cost is 1000 and the traveling cost is 1 per unit distance. The optimal solution to this example is to use a single vehicle to perform the schedule given in Table 2. After performing trip 1, the vehicle visits the recharging station with a remaining battery of 5. According to the timetable, there is a surplus of time to recharge partially for extra 20 units, which

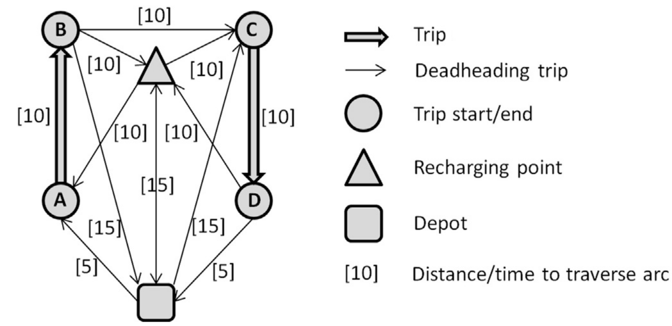


**Fig. 1.** A small E-VSP example with single depot, two trips and one recharging station.

**Table 1**
The timetables associated with the two trips in the small example.

| Trip | Origin | Time | Destination | Time |
|---|---|---|---|---|
| 1 | A | 07:50 | B | 08:00 |
| 2 | C | 08:40 | D | 08:50 |

**Table 2**
The optimal solution to the small example.

| Location | Arrival time | Departure time | Arrival fuel level | Departure fuel level | Accumulated cost |
|---|---|---|---|---|---|
| Depot | – | 7:45 | – | 30 | 0 |
| A | 7:50 | 7:50 | 25 | 25 | 5 |
| B | 8:00 | 8:00 | 15 | 15 | 15 |
| Recharging station | 8:10 | 8:30 | 5 | 25 | 25 |
| C | 8:40 | 8:40 | 15 | 15 | 35 |
| D | 8:50 | 8:50 | 5 | 5 | 45 |
| Depot | 8:55 | – | 0 | 0 | 50 |