



Innovative Applications of O.R.

The Electric Fleet Size and Mix Vehicle Routing Problem with Time Windows and Recharging Stations

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ARTICLE INFO

Article history:

Received 2 March 2015

Accepted 20 January 2016

Available online 27 January 2016

Keywords:

Heterogenous fleet

Electric vehicle routing

Efficient constraint handling

ABSTRACT

Due to new regulations and further technological progress in the field of electric vehicles, the research community faces the new challenge of incorporating the electric energy based restrictions into vehicle routing problems. One of these restrictions is the limited battery capacity which makes detours to recharging stations necessary, thus requiring efficient tour planning mechanisms in order to sustain the competitiveness of electric vehicles compared to conventional vehicles. We introduce the Electric Fleet Size and Mix Vehicle Routing Problem with Time Windows and Recharging Stations (E-FSMFTW) to model decisions to be made with regards to fleet composition and the actual vehicle routes including the choice of recharging times and locations. The available vehicle types differ in their transport capacity, battery size and acquisition cost. Furthermore, we consider time windows at customer locations, which is a common and important constraint in real-world routing and planning problems. We solve this problem by means of branch-and-price as well as proposing a hybrid heuristic, which combines an Adaptive Large Neighbourhood Search with an embedded local search and labeling procedure for intensification. By solving a newly created set of benchmark instances for the E-FSMFTW and the existing single vehicle type benchmark using an exact method as well, we show the effectiveness of the proposed approach.

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1. Introduction

Current research in sustainable and energy efficient mobility is strongly motivated by increasing concerns about climate change and rising green house gas emissions. The introduction of electrically powered vehicles is one of the major directions taken in order to address these concerns. Pure battery electric vehicles, as studied in this work, are only powered by an electric engine, using the energy stored in a rechargeable battery. One of the main operational challenges in transport applications is their limited range and long recharging times. Besides acquisition cost, the acceptance of electric vehicles in the transportation business will strongly depend on methods alleviating the range and recharging limitations. Selecting the right vehicles for specific transport requirements while minimizing overall cost is therefore of crucial importance.

Companies have a variety of available electric vehicles with certain variability concerning range, payload, and price to consider (see e.g., [Austriatech, 2014](#)). Especially with electric vehicles, acquisition cost play an important role in economic considerations of fleet managers. This means that larger vehicles might be able to serve the transportation needs without recharging operations. But the difference in price, using smaller vehicles in the fleet mix could reduce the overall cost. However, smaller vehicles have a smaller capacity and battery size, thus need to be recharged in order to serve longer tours, which in turn takes time. It is to be expected that smaller and cheaper vehicles will be used alongside larger vehicles depending on the typical customer distribution over the urban area. In this work we will show that a fleet composed of different vehicle types can indeed be beneficial.

We propose to address this task by introducing a new optimization problem, the so-called *Electric Fleet Size and Mix Vehicle Routing Problem with Time Windows and Recharging Stations* (E-FSMFTW). It combines and subsumes the well known Fleet Size Mix Vehicle Routing Problem with Time Windows (FSMFTW) and the recently defined Electric Vehicle Routing Problem with Time Windows and Recharging Stations (E-VRPTW).

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1.1. Related work

Solving and optimizing problems involving tour assignments of vehicles is a well known and well studied field of research, known as *Vehicle Routing Problem* (VRP) (Toth & Vigo, 2014). The basic problem variant is the *Capacitated VRP* (CVRP), where each customer has a given demand that has to be satisfied, with respect to a maximum vehicle capacity. The *VRP with Time Windows* (VRPTW) extends the CVRP by adding time windows to the depot and the customers. A survey on this problem class is provided in Bräysy and Gendreau (2005a, 2005b), Toth and Vigo (2014).

The classical VRP has been extended in various ways to account for additional real world aspects. These more complicated problems are often called “rich VRPs” or “multi-attribute VRPs”; see Vidal, Crainic, Gendreau, and Prins (2013a). Our research combines two such streams of research, (1) the use of electrical/zero-emission vehicles in “green” VRPs and (2) the analysis of VRPs with heterogeneous fleet. The first stream is part of research in the field of green logistics. A general survey on the subject is provided in Sbihi and Eglese (2010) and Dekker, Bloemhof, and Mallidis (2012). A recent discussion on electric vehicles for distribution goods is provided by Pelletier, Jabali, and Laporte (2015). For a summary of the work on non-electric “green” VRPs, minimizing for example emissions by speed optimization, we refer to Toth and Vigo (2014) as well.

Erdoğan and Miller-Hooks (2012) started by extending the CVRP to the *Green VRP* where tours for Alternative Fuel Vehicles are optimized. The uneven distribution of *Alternative Fuelling Stations* (AFS) leads to the problem of deciding when a vehicle has to visit AFS during its tour (possibly multiple times) in order to minimize the distance travelled but avert to run out of fuel. Two construction heuristics are presented: a *Clarke and Wright savings heuristic* (Clarke & Wright, 1964) that is extended to include AFS nodes during the merge process, and a *Density Based Clustering* exploiting spatial properties of the problem. Both approaches terminate after creating a solution containing a feasible set of routes, which is then improved by means of local search. The methods were tested on a randomly generated test set as well as a real world case study considering up to 500 (randomly located) customers and 21 existing AFS. For smaller random instances the presented methods obtain solutions that are, on average, less than 10% worse than the best known solutions obtained with CPLEX.

Schneider, Stenger, and Goeke (2014) adapted the Green VRP to electric vehicles (EV) and added time window constraints, introducing the *Electric VRPTW with Recharging Stations* (E-VRPTW). The aim is to find tours satisfying charge constraints (the state of charge may never fall below zero) and time window constraints. The recharging process complicates the time calculations, since the required recharging time depends on the state of the charge. The problem is solved by a *Variable Neighbourhood Search* (VNS) approach using *Tabu Search* (TS) as local optimization technique. The proposed approach was tested on a new benchmark set based on the traditional Solomon instances for the VRPTW that have been extended with recharging stations as well as the instances of Erdoğan and Miller-Hooks (2012) for the GreenVRP. In addition, the presented approach has been adapted to solve instances of the related *Multi Depot VRP with Inter-depot routes* (MDVRPI) (Crevier, Cordeau, & Laporte, 2007; Tarantilis, Zachariadis, & Kiranoudis, 2008), where vehicles can visit depots between customers to restock in order satisfy the demand of the customers. The presented methods were able to improve upon previous results for the GreenVRP and new best solutions have been obtained for the MDVRPI. Based on the proposed benchmark set, smaller instances allowing a direct comparison with CPLEX have been created. The comparison shows, that the VNS/TS approach is able to find optimal solutions (where known).

A different electric vehicle routing problem has been presented in Conrad, Figliozzi, Doolen, and Aken (2011), the so-called *Recharging VRP* (RVRP). Instead of using dedicated recharging stations the authors assume that a set of customers provides the option to recharge at their location. The EV can perform a recharging operation to a certain percentage of the maximum capacity, a so-called ‘quick charge’. It is assumed that this takes a fixed amount of time, independent of the current level of charge. Recharging operations and service at the customer can be performed simultaneously. Different problem instances are proposed and solved with various parameter settings using a modified iterative construction and improvement algorithm. The paper focuses on the analysis of the instance parameters and their contribution to the solutions obtained to generate meaningful solution bounds for the average tour distance.

Recently, Goeke and Schneider (2015) studied a rich fleet mixing problem where not only conventional and electric vehicles are considered, but also load-dependent energy consumption based on a real-world network. They developed an Adaptive Large Neighbourhood Search approach with an embedded local search procedure using an surrogate function to evaluate changes efficiently. In parallel to our work, Desaulniers, Fausto, Irnich, and Schneider (2014) tackled the original E-VRPTW as well as variations concerning variable recharging or allowing a single stop. They proposed a branch-price-and-cut algorithm with efficient labeling and cutting procedures applicable for all studied variants. In their computational results, they showed that their approach is able to solve instances with up to 100 customers, while some instances with 50 customers cannot be solved to optimality.

The second stream of research related to our work is that of VRPs with heterogeneous fleet. The *Mixed Fleet* or *Heterogenous VRP* considers problems where different types of vehicles are available. It was first introduced in Golden, Assad, Levy, and Gheysens (1984). Baldacci et al. (2008) identifies five major subclasses differing in the number of vehicles available (limited, unlimited), whether a fixed cost per vehicle is considered or not and if the routing cost depend on the vehicle type. The original formulation by Golden et al. (1984) considers an unlimited number of vehicles with fixed acquisition costs and vehicle type independent routing costs, which is classified as a *Fleet Size and Mix VRP with Fixed costs* (FSMF) (Baldacci et al., 2008; Toth & Vigo, 2014).

Liu and Shen (1999) reformulate the FSMF to consider time windows, creating the *Fleet Size and Mix Vehicle Routing Problem with Time Windows* (FSMFTW). The so-called *En Route* time, i.e., the time between departing from and returning to the depot minus the cumulative service time at the customers in the respective route is considered as routing cost. The proposed approach was applied to a new benchmark set based on the well known Solomon instances for the VRPTW. This benchmark extends the 56 VRPTW instances by providing three classes of vehicle type settings (A,B,C) varying from 3 to 6 vehicle types with different cost and capacity margins, resulting in 168 problem instances in total.

Bräysy, Dullaert, Hasle, Mester, and Gendreau (2008a) propose a three phase *multi-start deterministic annealing* metaheuristic (MSDA) to solve the FSMFTW. A threshold acceptance criterion is used where the maximum threshold of accepting a worse solution is reduced after a number of iteration until no worsening is allowed. The solution itself is created using a systematic and deterministic multi-phase approach, starting with a modified *Clarke and Wright savings heuristic*, followed by a route elimination procedure and a systematic local search where three operators are applied every single, second or third iteration. The proposed algorithm shows a very good performance when run for a similar amount of time compared to previous approaches. Furthermore, with longer run-times new best solutions for almost every instance are obtained.

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