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Discrete Optimization

Routing a mixed fleet of electric and conventional vehicles

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ABSTRACT

In this paper, we propose the Electric Vehicle Routing Problem with Time Windows and Mixed Fleet (E-VRPTWMF) to optimize the routing of a mixed fleet of electric commercial vehicles (ECVs) and conventional internal combustion commercial vehicles (ICCVs). Contrary to existing routing models for ECVs, which assume energy consumption to be a linear function of traveled distance, we utilize a realistic energy consumption model that incorporates speed, gradient and cargo load distribution. This is highly relevant in the context of ECVs because energy consumption determines the maximal driving range of ECVs and the recharging times at stations. To address the problem, we develop an Adaptive Large Neighborhood Search algorithm that is enhanced by a local search for intensification. In numerical studies on newly designed E-VRPTWMF test instances, we investigate the effect of considering the actual load distribution on the structure and quality of the generated solutions. Moreover, we study the influence of different objective functions on solution attributes and on the contribution of ECVs to the overall routing costs. Finally, we demonstrate the performance of the developed algorithm on benchmark instances of the related problems VRPTW and E-VRPTW.

1. Introduction

In Europe, recent years have seen a steady increase in energy costs while more and more laws are passed to regulate the emission of greenhouse gases in the transportation sector. These external factors and the society's rising environmental and social awareness have triggered numerous green initiatives at companies. In the logistics field, electric commercial vehicles (ECVs) are now considered a serious alternative to conventional internal combustion commercial vehicles (ICCVs). ECVs have no local greenhouse gas emission and produce only minimal noise, however, they are currently hardly competitive with ICCVs from a cost point of view (Davis & Figliozzi, 2013). Nevertheless, several companies have started to employ ECVs in their last-mile delivery operations, e.g., in the field of small-package shipping (Kleindorfer, Neboian, Roset, & Spinler, 2012) or the distribution of food (National Renewable Energy Laboratory, 2014) and beverages (Heineken International, 2014). Moreover, governments and private companies are starting to provide the required infrastructure to further boost this electrification trend (International Energy Agency, 2012, 2013; Tesla Motors, Inc., 2014).

One important aspect to render ECVs more competitive is to consider their special characteristics – a limited driving range and the potential need to recharge en route – in the planning of last-mile delivery operations employing ECVs. These distribution tasks are generally represented as vehicle routing problems (VRPs), whose goal is to find minimum-cost routes to serve a given set of customers from a central depot (Toth & Vigo, 2014). The first VRPs to address ECVs (or alternative fuel vehicles) with a limited driving range and the possibility of recharging (refueling) at dedicated stations have recently been presented in the literature (Conrad & Figliozzi, 2011; Erdogan & Miller-Hooks, 2012; Schneider, Stenger, & Goeke, 2014). Although two important constraints of last-mile delivery operations, namely vehicle capacity constraints and customer time windows have already been considered (Conrad & Figliozzi, 2011; Schneider, Stenger, & Goeke, 2014), many relevant real-life constraints are not yet covered by routing models for ECVs and dedicated solution methods.

In this work, we consider two important aspects for route planning with ECVs:

Mixed fleet: Most companies do not operate pure ECV fleets but are gradually introducing ECVs into their existing ICCV fleet. Therefore, our route planning method is able to handle a mixed fleet of ECVs and ICCVs. Compared to ICCVs, energy costs for operating ECVs are generally lower while labor costs may increase due to time spent on potentially necessary recharging activities along the routes. Energy and labor costs are among the main components of total operating costs (see, e.g., Bektaş & Laporte, 2011), so

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high-quality route planning with a mixed vehicle fleet has to consider the cost tradeoff between the two vehicle types.

Energy consumption: Real-life energy consumption is not a linear function of traveled distance as assumed in the models of Erdogan and Miller-Hooks (2012) and Schneider, Stenger, and Goeke (2014). We use realistic energy consumption functions of ECVs and ICCVs that incorporate vehicle speed, gradients and cargo load. In recent years, realistic energy consumption models have started to play an important role in routing models that consider fuel costs and vehicle emissions (Bektaş & Laporte, 2011; Jabali, Van Woensel, & de Kok, 2012). In the context of ECVs, energy consumption determines electricity costs on the one hand, but, more importantly, also the driving range of an ECV and thus the latest possible moment at which a recharge has to take place in order to prevent an ECV from getting stranded.

We propose the Electric VRP with Time Windows and Mixed Fleet (E-VRPTWMF) to determine optimal routes (according to different alternative objective functions considered in this work) for a given mixed fleet of ECVs and ICCVs. E-VRPTWMF incorporates time window and vehicle capacity constraints. We assume that ECVs can be recharged at any of the available stations causing a recharging time that depends on the battery level on arrival at the station. The energy consumption of ICCVs is calculated by means of the model presented in Demir, Bektaş, and Laporte (2012) and we extend this model to compute the battery energy consumption of ECVs.

As E-VRPTWMF extends the notoriously hard-to-solve VRPTW, exact methods will not be able to solve instances of realistic size within fast computation times. Therefore, we develop a heuristic solution method to address the problem, namely an Adaptive Large Neighborhood Search (ALNS) enhanced by a Local Search (LS) for intensification. Besides new operators considering recharging stations, our ALNS features several new ideas: (i) an adaptive mechanism to choose the number of customers to be removed in each iteration, (ii) the use of surrogate violations in order to handle the complexity of calculating time window and battery capacity violations, and (iii) an acceptance criterion taking into account the different penalty factors that were used when calculating the objective value of the solutions to be compared.

In numerical studies, we assess the performance of our ALNS on benchmark instances of related problems: ALNS achieves convincing results on the well-studied VRPTW benchmark of Solomon (1987), and outperforms previous methods on the E-VRPTW benchmark set of Schneider, Stenger, and Goeke (2014). In addition, we generate a set of new E-VRPTWMF instances based on the Pollution Routing Problem (PRP) benchmark of Demir et al. (2012). In experiments on these newly designed instances, we find that consideration of the actual load strongly improves the quality of the generated solutions in comparison to solutions that are generated based on load estimates. Moreover, we find that a large number of solutions that are generated with "optimistic" load estimates are actually infeasible due to battery capacity or time window violations. We further show that our ALNS works effectively with all of the investigated cost functions and that the traditional objective of minimizing traveled distance fails to produce high-quality solutions if routing costs including energy, labor and battery depreciation are considered. The choice of objective function additionally has a strong influence on the level of usage of the ECVs in the fleet.

This paper is organized as follows: In Section 2, we briefly review the literature related to E-VRPTWMF. Section 3 introduces the energy consumption models for ECVs and ICCVs. Section 4 presents a mixed-integer program of E-VRPTWMF. The ALNS is detailed in Section 5. The parameter setting, the generation of new E-VRPTWMF instances and the numerical studies on the new instances and on the test instances of related problems are presented in Section 6. Section 7 summarizes and concludes the paper.

2. Literature

In the following, we discuss the literature related to the E-VRPTWMF. First, we review works on routing alternative fuel vehicles. Second, VRP papers that explicitly model energy consumption or account for the impact of load distribution are presented. Third, we discuss other related fields.

Conrad and Figliozzi (2011) study the Recharging VRP, in which vehicles with limited range can recharge at certain customer locations. Time window constraints are considered and a fixed recharging time is assumed. The authors compute bounds to predict average tour lengths and study the impact of driving range, recharging times, and time window existence. Erdogan and Miller-Hooks (2012) propose two heuristics for the Green VRP. In this problem, alternative fuel is only available at dedicated points that have to be visited en route. Refueling time is assumed fixed and no capacity or time window constraints are included. Other works addressing the Green VRP or extensions of this problem are (Felipe, Ortuño, Righini, & Tirado, 2014; Montoya, Guéret, Mendoza, & Villegas, 2014; Schneider, Stenger, & Hof, 2014). Schneider, Stenger, and Goeke (2014) develop a hybrid of Variable Neighborhood Search (VNS) and Tabu Search (TS) to address E-VRPTW, in which ECVs with a limited battery capacity may visit recharging stations en route, and customer time windows and vehicle capacities have to be respected. Recharging time is proportional to the amount of energy required to recharge the battery to full capacity. Desaulniers, Errico, Irnich, and Schneider (2014) present branch-price-and-cut algorithms to address four variants of the E-VRPTW. In a recent working paper, Hiermann, Puchinger, and Hartl (2014) combine the E-VRPTW and the Fleet Size and Mix VRP with Fixed costs (FSMF). In the resulting E-FSMVRPTW an unlimited number of ECVs with different battery capacities and vehicle-independent routing costs are available. Cost-optimal routes are determined by means of an ALNS enhanced by a labeling algorithm. Barco, Guerra, Muñoz, and Quijano (2013) propose a comprehensive approach for planning the deployment of electric vehicles in an airport shuttle service. They first determine a minimal consumption graph, on which routing decisions under consideration of a limited battery capacity are made. The assignment of vehicles to routes and the scheduling of recharges is determined by an evolutionary algorithm. Finally, Preis, Frank, and Nachtigall (2014) investigate an ECV routing model with customer time windows, fixed recharging times, and the goal of minimizing total energy consumption, which depends on gradients and cargo load. A simple TS algorithm based on a relocate operator is presented.

The second strand of relevant literature integrates energy considerations and the resulting fuel consumption and emissions of ICCVs into routing models. Bektaş and Laporte (2011) propose the PRP, in which they estimate the price of pollution and introduce it as part of the objective function, besides costs for driver wages and fuel consumption. They allow the choice between different speed levels for arcs and consider speed, gradients, and load to calculate the fuel consumption and corresponding emissions. Demir, Bektaş, and Laporte (2011) provide a comparison of vehicle emission models. Demir et al. (2012) propose an ALNS and a speed optimization algorithm for the PRP. Computational experiments show moderate run-times for problem sizes with 200 customers. Demir, Bektaş, and Laporte (2014a) address a bi-objective function for the PRP that models the conflicting targets of minimizing driver time and usage of fuel and thus avoid the problematic representation of emissions in terms of monetary cost. An extensive review of related literature can be found in Demir, Bektaş, and Laporte (2014b). Kopfer, Schönberger, and Kopfer (2014) use CPLEX to solve a heterogeneous VRP with the objective of minimizing fuel consumption. To this end, the authors derive linear relationships