Transportation Research Part B 99 (2017) 138–166

Contents lists available at ScienceDirect

Transportation Research Part B

journal homepage: www.elsevier.com/locate/trb

Network user equilibrium problems for the mixed battery electric vehicles and gasoline vehicles subject to battery swapping stations and road grade constraints

Min Xu[a], Qiang Meng[a,*], Kai Liu[b]

[a] Department of Civil and Environmental Engineering, National University of Singapore, Singapore 117576, Singapore
[b] School of Transportation and Logistics, Dalian University of Technology, Dalian 116024, PR China

ARTICLE INFO

Article history:
Received 14 August 2016
Revised 20 November 2016
Accepted 18 January 2017
Available online 31 January 2017

Keywords:
User equilibrium
Battery electric vehicles
Battery swapping stations
Road grade
Flow-dependent electricity consumption

ABSTRACT

There has been growing attention on battery electric vehicles (BEVs) due to their energy efficiency and environmental friendliness. This paper deals with the user equilibrium (UE) problems for the mixed BEVs and traditional gasoline vehicles (GVs) in transportation networks with battery swapping stations and road grade constraints. Under the assumption that electricity consumption rate is not affected by traveling speed or traffic flow, a nonlinear minimization model in terms of path flows is first formulated by incorporating effects of road grade on the electricity consumption rate. The battery swapping action based paths are defined for BEVs in the represented network to facilitate the model building with flow-dependent dwell time at the battery swapping stations. The Frank-Wolfe (F-W) algorithm, where descent direction is found by the multi-label method in a pseudo-polynomial time, is adopted to solve the model. Moreover, the aforementioned assumption about the flow-independent electricity consumption rate is then relaxed and a system of inequalities has been proposed to formulate the UE conditions. For the nonlinear minimization model, two numerical examples are presented to assess the propose model and algorithm, as well as to analyze the impact of usable battery capacity, BEVs' market share and some attributes of battery swapping stations on the equilibrium link flows and/or swapping flows. The system of inequalities is exactly solved for a small network by path enumeration to demonstrate the non-uniqueness of UE link flow solutions.

1. Introduction

Compared with the conventional gasoline vehicles (GVs), the battery electric vehicles (BEVs) deliver many benefits like low greenhouse gas (GHG) emission and high energy efficiency (Berr, 2008; Duvall, 2007). Plug-in charging and battery swapping are two prevailing technologies for BEVs to get a depleted battery refreshed. The former one recharges BEVs at home or charging stations and the latter replaces a depleted battery with a fully charged one at the battery swapping stations. The scarce charging infrastructure and long charging time, however, hinder the adoption of BEVs on a mass scale (Charles Botsford, 2009). The limited driving range of fully-charged BEVs further reduces public incentive to purchase BEVs because they have to frequently recharge their BEVs during a long journey. To address this issue, more charging stations or battery swapping stations have to be deployed in a transportation network.

* Corresponding author.
E-mail address: ceemq@nus.edu.sg (Q. Meng).

http://dx.doi.org/10.1016/j.trb.2017.01.009

The routing behaviors of BEV drivers in a transportation network with battery charging and swapping stations are essentially different. Although under both circumstances, the drivers select the efficient routes to reach the charging or swapping stations if they are in need of charging/swapping, the tradeoff between charging time and charging amount should be balanced exclusively at the battery charging stations. In reality, battery swapping is equivalent to charging a predefined amount of electricity at the battery charging stations from the aspect of modeling, where the charging amount is pre-specified parameter known by drivers rather than a decision variable made by them.

Typically, a fast changing station takes about 35 min to replenish a depleted battery of 35 kW h even with a power level as high as 60 kW (ETEC, 2010), whereas the BEV drivers may exchange their depleted battery within two or three minutes at a swapping station (Mak et al., 2013). In other words, the battery swapping is more efficient than battery charging in terms of the time to replenish energy. This advantage has made BEVs comparable to GVs since the time to swap the battery of a BEV is almost the same with or even less than the time to fill the tank of a GV. In addition, batteries with highest energy density (potentially with longest driving range) are promising candidates for battery swapping due to their unique process to get replenished (EC, 2007). Moreover, as elaborated previously, battery swapping is equivalent to charging a BEV fully or for a predefined amount of electricity. With the great improvements in science and technology, advanced batteries with higher energy density and charging methods with less charging time may come to the market in the foreseeable future. For example, researchers from Singapore have developed an ultra-fast charging battery which can get 70% of its battery capacity recharged in only two minutes (NTU, 2014). Once this technology becomes mature, there would be almost no difference between battery charging and swapping stations because drivers would charge their batteries fully considering the negligible charging time. Hence, this study aims to model the user equilibrium (UE) behaviors of BEVs in their route choice with the battery swapping stations.

Given the long charging time, limited driving range and charging infrastructure, both BEVs and GVs will coexist in the transportation networks for a long time. The behaviors of BEV and GV drivers in their route choice from an origin to a destination are distinct because the BEV drivers have to exchange batteries at the battery swapping stations during their journeys. In addition, the fear of running out of electricity before reaching their destinations or battery swapping stations, referred to as *range anxiety* (Eberle and von Helmolt, 2010; Pearre et al., 2011), will make their route choice decision process more complicated. It is well recognized that road grade has significant impact on the energy consumption of BEVs (Frey et al., 2008; Liu et al., 2015; Travesset-Baro et al., 2015) and more electricity will be consumed on a road with steep upslope and vice versa. As a result, the road grade will inevitably affect the driving range, the range anxiety and route choice in turn for BEVs. This study, therefore, focuses on model development and algorithm design for the UE problems in a transportation network running both BEVs and GVs subject to the battery swapping station and road grade constraints.

1.1. Literature review

UE problem is a fundamental and important problem for transportation planning. It aims to predict the traffic flow under the assumption that all the travelers make their route choice by selecting the path with minimal travel cost (Wardrop, 1952). Apart from its wide application in road congestion pricing (Yang and Huang, 2005; Meng et al., 2012), network design problems (Yang and Bell, 1998; Wang et al., 2013; Ban et al., 2006) etc., over the past decades, researchers have made several extensions by relaxing the aforementioned assumption and incorporating more realism into the traditional UE. The prominent examples include the stochastic user equilibrium (SUE) (Daganzo and Sheffi, 1977; Meng and Liu, 2012) and boundedly rational user equilibrium (BRUE) (Di et al., 2013; Di and Liu, 2016; Lou et al., 2010). Most of these studies focused on the UE problem of GVs. As for BEVs, Jing et al. (2016) have recently provided a comprehensive review for the network modeling of BEVs, where UE problem with BEVs is particularly discussed. In view of the focus of this study, we only review the relevant studies on the UE problems with BEVs. The other studies, including the BEV touring, routing and scheduling problems (Liao et al., 2016; Adler et al., 2016; Adler and Mirchandani, 2014; Schneider et al., 2014), the market penetration and climate impact analysis of BEVs (Egbue and Long, 2012; Yabe et al., 2012) and the optimal deployment of recharging or swapping stations (He et al., 2013; Mak et al., 2013; Nie and Ghamami, 2013; Sathaye and Kelley, 2013; He et al., 2015; Ghamami et al., 2016; Li et al., 2016), will not be covered by the literature review presented below.

Jiang et al. (2012), Jiang et al. (2014) and Jiang and Xie (2014) proposed three distance-constrained UE models for the transportation networks running both BEVs and GVS without the charging station constraint under different problem settings. They applied the Frank–Wolfe (F–W) method, projected gradient method, and the partial linearization method incorporating with a special weight constrained shortest path problem (WCSPP) for solving their distance-constrained UE models. To be more specific, Jiang et al. (2012) put forward a Frank–Wolfe method with the label-setting method solving the WCSPP (FW-WCSPP) for the distance-constrained UE model. Jiang and Xie (2014) used the Frank–Wolfe algorithmic framework with a modified one-to-all label-setting method (FW-MLS) as well as the projected gradient method with a combined preprocessing and label-setting method (PG-PLS) respectively, for solving the combined UE model with distance constraints. They later employed the partial linearization method with a combined pre-processing and label-setting method (PLM-PLS) to solve another combined and distance-constrained UE model.

The number of aforementioned studies made by Jiang and his research collaborators does not take into account locations of charging or swapping stations over a network. He et al. (2014) made the first attempt to investigate the UE problem with the plug-in charging stations, where BEV drivers decide where and how much to charge their BEVs. They built a convex programming model for the UE problem when the recharging time are considered and developed an iterative algorithm for