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Data-driven optimal charging decision making for connected and automated electric vehicles: A personal usage scenario

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ABSTRACT

This study introduces an optimal charging decision making framework for connected and automated electric vehicles under a personal usage scenario. This framework aims to provide charging strategies, i.e. the choice of charging station and the amount of charged energy, by considering constraints from personal daily itineraries and existing charging infrastructure. A data-driven method is introduced to establish a stochastic energy consumption prediction model with consideration of realistic uncertainties. This is performed by analyzing a large scale electric vehicle data set. A real-time updating method is designed to construct this prediction model from new consecutive data points in an adaptive way for real-world applications. Based on this energy cost prediction framework from real electric vehicle data, multistage optimal charging decision making models are introduced, including a deterministic model for average outcome decision making and a robust model for safest charging strategies. A dynamic programming algorithm is proposed to find the optimal charging strategies. Detailed simulations and case studies demonstrate the performance of the proposed algorithms to find optimal charging strategies. They also show the potential capability of connected and automated electric vehicles to reduce the range anxiety and charging infrastructure dependency.

1. Introduction

Electrification of transportation by increasing electric vehicle (EV) usage has important impacts on greenhouse gas emissions and energy dependency (Sioshansi and Denholm, 2009; Eberle and Von Helmolt, 2010; Armaroli and Balzani, 2011). Tremendous work is being performed to electrify powertrain systems and the transportation system (Bilgin et al., 2015). Accelerating EV adoption may be a key strategy for helping regions achieve national- and state-level transportation sustainability. Besides great progress in electric drive systems, recently most automakers and some high-tech companies, e.g. Google, Uber, etc., are focusing on implementing autonomous driving technology. They are trying to put forward the real-world application of this technology. Furthermore, the automotive OEMs are combining autonomous driving technology with electric vehicles. For example, all Tesla cars being produced now have full self-driving hardware (Tesla, 2016). General Motors is also testing the autonomous driving on its new Chevrolet Bolt (electrek, 2017). Only a few of them are named here. Car-sharing or car-hailing companies plan to use both electric vehicles and autonomous driving in their transportation network. Self-driving technology is an important aspect to improve their service quality and reduce operation costs. Electrified vehicles can help to improve the energy efficiency. These two trends will work together to improve the intelligence and sustainability of transportation system in the coming future.

Current electric vehicles still have the essential barrier of long charging time compared to conventional vehicles. Relative high

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costs are necessary for satisfying charging requirements. For example, the construction cost of charging stations, the long charging time for EV user, etc. However, the introduction of autonomous driving technology would remove the challenge of co-locating charging infrastructure with driver destinations and presents a driver-free method for EVs to reach nearby charging stations. This will significantly change the charging behavior of electric vehicles. EV driver will no longer need to be present at charging stations for charging actions. Automated EVs can drive to nearby charging stations to perform charging actions by themselves when necessary. Meanwhile, connected vehicles technology is emerging to make real-time connections between vehicles and infrastructure networks. Electric vehicles will have the capability to sense and obtain pertinent information from nearby charging station networks and then calculate the corresponding costs and availability for charging. This information will be very helpful for real-time, optimal and sustainable charging decision-making for electric vehicles. It has to say that autonomous vehicle technology cannot solve all the city transportation problem as discussed in UITP (2017). However, it has huge potential to improve the convenience and sustainability of EV charging actions.

This study attempts to establish an optimal and sustainable charging decision-making framework for connected and automated electric vehicles (CAEVs). The personal usage scenario of CAEVs with time and distance constraints of daily itineraries is the main focus in this paper. The objective of this framework aims to design optimal charging strategies for minimum charging cost (e.g. monetary cost) outside home and also minimization of travel or energy cost attributed to charging actions. More details will be introduced in the following sections. This paper is organized as follows: Section 2 provides the related previous research and also our contributions in this paper. Section 3 introduces a multi-channel stochastic energy consumption prediction model and the corresponding real-time updating algorithm based on the data-driven method. Based on the energy cost prediction model, multistage optimal charging decision-making models are proposed in Section 4. Section 5 proposes a dynamic programming procedure for optimal charging strategies. Simulations and case studies in Section 6 are used to demonstrate the introduced framework. Section 7 concludes our work in this paper and also discusses some potential future research.

2. Previous research and our contributions

Charging decision making for electric vehicles includes several aspects, e.g. the deployment of charging infrastructure, the analysis of charging behavior and the design of charging strategies. A lot of research has been performed for charging station deployment and charging behavior analysis. Different methods have been introduced for charging station deployment according to specific requirements and realistic situations, for example, deployment of both stationary and dynamic charging infrastructure for electric vehicles along traffic corridors in Z. Chen et al. (2017), data-driven method for siting and sizing of electric taxi charging stations in Yang et al. (2017), charging station deployment on urban road network in He et al. (2015, 2016), Giménez-Gaydou et al. (2016), Frade et al. (2011), Yi and Bauer (2016a), activity-based approach in Dong et al. (2014), and many more, e.g. Xylia et al. (2017), Tu et al. (2016), Ghamami et al. (2016), Li et al. (2016), etc. Deployment methods of wireless charging facilities are also being investigated in current literature, for example, Z. Chen et al. (2017), Deflorio and Castello (2017), Fuller (2016), Riemann et al. (2015). For charging behavior analysis, two multinomial logit-based and two nested logit-based models are proposed in Yang et al. (2016) for modeling the charging and route choice behavior of BEV drivers. The behaviors of electric vehicle driver and parking pattern are analyzed in Marmaras et al. (2017), Latinopoulos et al. (2017), and Birrell et al. (2015). In contrast to a large body of literature on charging station deployment and charging behavior analysis, studies looking at the design of charging strategies of electric vehicles in a connected and fully automated setting are more limited.

The topic of optimal charging decision making in this paper focus on the design of charging strategies. It is also part of smart charging, which improves the interactions among the smart grid and EVs. Smart charging has been investigated thoroughly in previous research from different aspects. Most of them focused on the interaction with the power grid, for example, the smart energy supply (Wang et al., 2016) and the impact of charging action on the power grid (Sundstrom and Binding, 2012; Hu et al., 2014). However, smart charging management from the viewpoint of the electric vehicle is also a very important aspect for EV users. The problem studied in this paper can be considered as trip level charging management for travel demand. An intelligent and sustainable way to charge is crucial to improve the driving experience and reduce the range anxiety of electric vehicle users. But there is little research about this topic. Most topics focused on the energy demand estimation (Bae and Kwasinski, 2012; Yi and Bauer, 2016b) or existing charging behavior analysis (Marmaras et al., 2017; Latinopoulos et al., 2017; Yang et al., 2016; Birrell et al., 2015; Smart and Schey, 2012). This is because most current charging decisions are made by EV owners according to their experiences and driving demand. A charging decision-making system for current personal EV usage is not as important as other problems. There is some research on charging decision making in the fleet management system, for example the work in T. Chen et al. (2016) and Pourazarm et al. (2016). Charging strategy is a relatively more important aspect in EV fleet operation than for individual users. It aims to make sure an EV fleet can always have enough energy to perform services. However, this research doesn't investigate decision making by involving the autonomous driving setting. And there are different requirements for personal and fleet vehicle usage.

With the emerging of autonomous driving and its application in electric vehicles, the charging decision making should be taken over by the vehicles. Autonomous electric vehicles will require the capability to make charging decisions according to the battery energy state, the travel demand and also the available charging infrastructure. Automated electric vehicle charging stations will become available in the future (Corbett and Maniaci, 2013; Tesla, 2017). Some works have touched this topic under the car-sharing situation. The work in Fagnant and Kockelman (2014) describes the design of an agent-based model for shared autonomous vehicle (SAV) operations. T.D. Chen et al. (2016) further explores the management of a fleet of shared autonomous electric vehicles (SAEVs) in a regional, discrete-time, agent-based model. Although charging actions have been touched in this paper, the discussion for charging decision making is relatively initial. None of this previous work investigates the charging decision making for the connected