European Journal of Operational Research 000 (2015) 1–10

Contents lists available at ScienceDirect

European Journal of Operational Research

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

Stochastics and Statistics

Optimal routing for electric vehicle service systems

Ying-Chao Hung[a,*], George Michailidis[b]

[a] Department of Statistics, National Chengchi University, Taipei 11605, Taiwan
[b] Department of Statistics and Computer and Information Sciences, University of Florida, Gainesville, FL 32611-8545, USA

ARTICLE INFO

Article history:
Received 10 December 2014
Accepted 8 June 2015
Available online xxx

Keywords:
Routing
Electric vehicle system
Maximum throughput
Perturbed Lyapunov function method
Sojourn time

ABSTRACT

There is increased interest in deploying charging station infrastructure for electric vehicles, due to the increasing adoption of such vehicles to reduce emissions. However, there are a number of key challenges for providing high quality of service to such vehicles, stemming from technological reasons. One of them is due to the relative slow charging times and the other is due to the relative limited battery range. Hence, developing efficient routing strategies of electric vehicles requesting charging to stations that have available charging resources is an important component of the infrastructure. In this work, we propose a queueing modeling framework for the problem at hand and develop such routing strategies that optimise a performance metric related to vehicles' sojourn time in the system. By incorporating appropriate weights into the well-known dynamic routing discipline "Join-the-Shortest-Queue", we show that the proposed routing strategies not only do they maximise the queueing system's throughput, but also significantly mitigate the vehicle's sojourn time. The strategies are also adaptive in nature and responsive to changes in the speed of charging at the stations, the distribution of the vehicles' point of origin when requesting service, the traffic congestion level and the vehicle speed; all the above are novel aspects and compatible with the requirements of a modern electric vehicle charging infrastructure.

1. Introduction

Over the last few years a strong push is occurring to reduce the use of hydrocarbons in the transportation sector. This trend is supported by the latest advances in battery and power electronics technology, along with government mandates on energy independence and resilience, as well as an increased emphasis on a smarter infrastructure. It is strongly enabled by the introduction of electric vehicles (EVs) and their close relatives Plug-in Hybrid Electric Vehicles (PHEVs) by major car manufacturers that have drastically increased consumer choices.

According to a recent report of the International Energy Agency (2012a), the transportation ‘ accounted for 6.7 gigatons of emitted CO_2 or 22 percent of the world's total. Further, global fuel demand for transportation is projected to grow approximately 40 percent by 2035 International Energy Agency (2012b), driven by the rapid adoption of automobiles in the fast growing economies of China, India and more recently in the African continent. EV/PHEVs represent an innovative technology that could help address both environmental concerns and longer term reduce dependence on fossil fuels. However, fast EV adoption relies on a number of socio-economic, as well as technological factors. Key socio-economic factors include stringent emissions regulations, rising fuel prices and financial incentive programs OECD/International Energy Agency (2013), while the most pressing technological one is the large scale *deployment* of an efficient and well managed charging station infrastructure. At present, there are diverging forecasts on the growth rate of the EV population International Energy Agency (2011), although there is consensus that it is going to represent a sizable portion (at least 7 percent in the US) of the national fleet by 2025–30. Obviously, penetration rates could be significantly higher than these estimates depending on how the aforementioned socio-economic and technological factors evolve. Further, the impact of fast adoption of EVs on utilities and on the stability of the grid is mostly dependent on regional or even local penetration rates; e.g., Southern California Edison has projected a penetration rate larger than 7 percent in its service territory already by 2020.

The key concern regarding rapid adoption of EVs by utilities is that they could have a disruptive impact on the power grid, since under Level 1 charging conditions, an EV represents a load equivalent to 50 percent of that of a house, while under Level 2 conditions it represents a 2.5-fold equivalent load. Obviously, the extent of their impact will depend on the degree and local/regional density of their penetration, charging requirements and the time of the day they are charged. However, studies have shown that a fleet of EVs can be effectively

* Corrsponding author. Tel.: +88 6229387115.
E-mail addresses: hungy@nccu.edu.tw (Y.-C. Hung), gmichail@ufl.edu (G. Michailidis).

http://dx.doi.org/10.1016/j.ejor.2015.06.013
0377-2217/

powered by the underutilised electric power grid during the off-peak hours with little need to increase the energy delivery capacity of the existing grid infrastructure (Taylor, Maitra, Alexander, Brooks, & Duvall, 2010) if scheduled carefully. Hence, the literature has focused on coming up with efficient schedules of charging EVs overnight, e.g. an incentive based energy consumption controlling scheme was introduced in Caron and Kesidis (2010), and a direct load control (DLC) scheme for residential energy control was discussed in Ruiz, Cobelo, and Oyarzabal (2009); Wu, Wang, and Goel (2010). To achieve a sustainable electrification of the transportation sector, a robust charging station infrastructure needs to be in place that would not interfere with regular grid operations and at the same time address EV driver's range anxiety resulting from the limited ability to recharge EVs in a time commensurable with filling the tank of a gas-powered vehicle. Specifically, UCLA Smart Grid Energy Research Center argues that if 25 percent of all vehicles were pure EVs, the current US power grid would be challenged in meeting the demand for power. For some utilities, even adding Level-2 charging infrastructure may overload distribution transformers during peak hours. On the driver's quality-of-service issue, note that charging EVs is an inherently slow process (it takes between 20 minutes to several hours to fully charge them, depending on the technology used (Lukic, Cao, Bansal, Rodriguez, & Emadi, 2008)), thus requiring careful planning and control to accommodate customers.

In this study, we focus on the development of efficient routing strategies for a general model of EV charging systems with fully random environments, so as to provide quality service to EV drivers and release their range anxiety. This directly leads to the goal of minimising the strategy's performance metrics related to "sojourn time" (including EV's travel time, waiting time for charging, and charging time), which is different from the well-known Vehicle Routing Problem (VRP) (Dantzig & Ramser, 1959; Pillac, Gendreau, Guéret, & Medaglia, 2013) and Dynamic Traveling Repairman Problem (DTRP) (Bertsimas & Ryzin, 1990, 1993) that involve design of vehicle-delivery routes from a depot to a set of scattered demand locations, so as to minimise the overall routing cost (e.g., travel time/distance) under various side constraints (Baldacci, Toth, & Vigo, 2007; Ferrucci, Block, & Gendreau, 2013; Jaillet & Wagner, 2008; Kergosien, Lenté, Piton, & Billaut, 2011; Laporte, 2007, 2009; Li, Mirchandani, & Borenstein, 2009; Pavone, Frazzoli, & Bullo, 2007; Pillac et al., 2013; Solomon, 1987). We assume that service demands are placed by the EV drivers according to a general process, and the distribution of the locations of where EVs originate is arbitrary, although its support is determined by a compact Euclidean service region. There are K charging stations located in the service region, and each of them has a known charging speed (usually in kiloWatt-hours). Upon the request of service, each EV is directed to one of the stations according to some routing policy and heads to the station at a constant speed. After entering the station, EVs queue up to be serviced and their charging times are assumed to be randomly distributed from an arbitrary distribution. We also assume that real-time communication between vehicles and the decision maker is possible (e.g., advanced mobile phones or global positioning systems (GPS) can be integrated into the vehicle devices). These flexible assumptions are suitable for real-life settings, but also require more complicated routing strategies (e.g., dynamic/online routing) for solving the designated optimisation problem.

Note that the way we formulate the problem allows us to depict the EV service system as an acyclic network with two layers of feed-forward parallel queues (see Section 2 for details), thus facilitating the development of routing strategies and fundamental analysis regarding throughput and stability. For example, it was shown that the dynamic routing strategy "Join-the-Shortest-Queue" (JSQ) along with a scheduling policy based on "maximal matching" maximises the throughput of a general acyclic network and achieves system stability defined by the uniform mean recurrence time (Hung & Michailidis, 2012). Although the EV system described here has different characteristics (see Section 2 for details), the JSQ strategy appears to retain the property of throughput maximisation (see Section 4 for details). However, to minimise a key performance metric -the vehicle's sojourn time in the system- the routing strategy must in addition be responsive to other system states and control parameters. In this work, we show that the vehicle's sojourn time can be significantly mitigated by incorporating the following two factors as "weights" into the JSQ policy: (i) the rate at which vehicles can be charged at the stations and (ii) the distance of the EV to each station upon its service request. Further, its performance is adaptive to the change of several control parameters, such as the speed of charging stations, the distribution of demand locations, the traffic congestion level, and the vehicle speed. It should be noted that the idea to integrate the elements of queue length, service rate and distance to the charging facility in the development of routing strategies for queueing systems has not been proposed in the literature, to the best of our knowledge.

The remainder of this paper is organised as follows. Section 2 depicts a general model for the EV service system with fully random environments, characterises the system's maximum throughput based on the capacity of each service station, and defines system stability via the uniform mean recurrence time property. Section 3 introduces some routing policies, some of which have been used in different settings in the literature, while others have to property of maximising the system's throughput. The performance of some of these policies is assessed numerically in Section 5. Section 4 establishes that the proposed weighted versions of JSQ policies indeed maximise the system's throughput under fairly weak stochastic assumptions on the arrival and service (charging) processes. Since appropriate dependence structures are allowed for the arrival, service, and routing processes, a technique called the "perturbed Lyapunov function method" (Hung & Michailidis, 2012; Kushner, 1967) was employed to obtain the result. Section 5 evaluates the proposed throughput-maximising policies in terms of their sojourn-time metrics under various control parameter settings through a simulation study. Some concluding remarks are presented in Section 6.

2. Model description and system stability

Suppose there are K EV charging stations placed in a compact Euclidean region $\mathcal{R} \subset \mathbb{R}^2$, whose locations are denoted by $S_1, S_2, \ldots, S_K$. Service demands for charging are placed by EV drivers at random locations in region $\mathcal{R}$ according to a general random process with rate λ, and we assume the demand locations follow an arbitrary distribution F over the region $\mathcal{R}$. Upon request of service, each EV is guided to one of the charging stations according to some routing policy π and heads to the station, for simplicity, at a constant speed $v > 0$. Note that the latter assumption is made to simplify the exposition, although in practice v can be a non-decreasing function of λ; e.g. one may imagine that vehicles slow down when the system is heavily loaded. We also assume that assigned EV routes do not change, while the EVs are in route to the assigned station. Finally, to simplify the formulation of the problem, we assume that each charging station comprises of an infinite buffer first-in-first-out (FIFO) queue and a charger with random service times. When the EV is charged (service completed), it leaves the system immediately.

Denote the set of EV service demand times by $\mathcal{A} = \{a_1, a_2, \ldots\}$ and the set of times that EVs have finished charging at the station by $\mathcal{D} = \{d_1, d_2, \ldots\}$. The collection of all event times is then denoted by $\mathcal{A} \cup \mathcal{D} = \{t_1, t_2, \ldots\}$, where t_i represents either the demand arrival or system departure time. If $t_i \in \mathcal{A}$, then its associated demand location is denoted by l_i, $l_i \in \mathcal{R}$. For any routing policy π, the associated routing process is given by

$$I_k(t_i) = \begin{cases} 1 & \text{if } t_i \in \mathcal{A} \text{ and the vehicle is directed to station } k, \\ 0 & \text{otherwise,} \end{cases} \tag{1}$$