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Optimal design of electric vehicle public charging system in an urban network for Greenhouse Gas Emission and cost minimization

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ABSTRACT

In this paper, we address the optimization problem of allocation of Electric Vehicle (EV) public fast charging stations over an urban grid network. The objective is to minimize Greenhouse Gas Emissions (GHG) under multiple constraints including a limited agency budget, accessibility of charging stations in every possible charging request and charging demands during peak hours. Additionally, we address bi-criteria problems to consider user costs as the second objective. A convex parsimonious model that depends on relatively few assumptions and input parameters is proposed and it is shown to be useful for obtaining conceptual insights for high-level planning. In a parametric study using a hypothetical urban network model generated based on realistic parameters, we show that GHG emissions decrease with agency budget, and that the reductions vary depending on multiple factors related to EV market and EV technologies. The optimal solutions found from the bi-criteria problems are shown to be close to the solution minimizing GHG emissions only, meaning that the emission minimizing policy can also minimize user costs.

1. Introduction

In the past few years, battery-powered Electric Vehicles (EVs) have emerged as sustainable transportation alternatives. In the United Arab Emirates, roadway transportation contributes to 33% of the national Greenhouse Gas emissions (Dincer et al., 2009; IPCC, 2013), and compared to petroleum-based vehicles that have been the predominant transportation mode for the last century EVs produce lower Greenhouse Gas (GHG) emission rate per unit travel time and distance. EVs produce zero GHG emissions during the operations phases, and when considering the entire lifecycle of batteries and the supply chain of electricity (Chester and Horvath, 2009), they still outperform petroleum-based vehicles for any electricity source (EPA, 2014; ANL, 2014; Nealer et al., 2015).

For roadway users, EVs have become increasingly attractive on account of government financial incentives, charging infrastructure (Sierzchula et al., 2014), fuel cost savings and maintenance cost savings due to the simplicity of design (Khaligh and Li, 2010; Li et al., 2016). As a result, the proportion of EVs in the total automobile fleet has gradually increased (IEA, 2016; EAFO, 2016; IHS Polk, 2014; MarkLines, 2016; ACEA, 2016; EEA, 2015). As noted by Sierzchula et al. (2014), the availability of the charging infrastructure is the strongest factor related to EV market share. Furthermore, even though EVs were first invented in the mid-19th century, demand was relatively negligible, so the existing charging infrastructure is not sufficient to meet increasing EV demand in the near future. Thus, installation of new charging infrastructure has become a critical issue for the future growth of the EV market share.

This paper addresses the optimization problem of allocating public EV charging stations with DC quick chargers spatially over an

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urban grid network. Specifically, the problem is the determination of station density and number of chargers per station, aiming to minimize Greenhouse Gas Emissions (GHG) under multiple constraints. These constraints include a limited agency budget and the condition that all drivers in the network are able to access it whenever they need. Currently, there exists a high level of uncertainty in EV technologies in terms of battery capacity and charging speed, as well as future demand. Therefore, parsimonious models that depend on relatively few assumptions and input parameters are useful, as they can provide conceptual insights that are useful for high-level planning, (Gabaix and Laibson, 2008). Daganzo et al. (2012) showed that parsimonious models have been effective for transportation design optimization. Thus, Sathaye and Kelley (2013) used parsimonious models for the optimal planning of EV fueling infrastructure for highway corridors to minimize the deviation from the original trips along the corridor. Their model needs few input parameters, which can be preferable to models that require many detailed inputs such as microscopic simulations and graph theory methodologies (e.g. Jia et al., 2012; He et al., 2013, 2015; Ghamami et al., 2016). Ahn and Yeo (2015) proposed an analytical planning model that is also parsimonious to estimate the optimal density of EV charging station for a grid urban network aiming to minimize total societal costs including deviation costs, queuing costs and installation and operating costs of charging stations. Both models require a small number of input parameters and have relatively low complexity, but they give conceptual insights such as the number of necessary fueling stations in a certain area under different levels of EV traffic demands.

Previous related studies solve the charging station planning problem to achieve societal needs but do not consider associated GHG emissions. This paper proposes a parsimonious model to find the optimal charging station planning aiming to minimize GHG emissions.

2. Problem formulation and solution methodology

In this section, we formulate the sustainable charging station planning problem and present a solution methodology. Suppose that there are N square cells in an urban grid network, and the area size of each cell $n \in \{1,\ldots,N\}$ is expressed as $L \times L$ (km^2). We assume that loop detectors are installed over each link in the network, so we can derive accumulation k_n (veh/km^2), the number of vehicles in 1×1 (km^2), and outflow rate q_n (veh/day/km^2), the number of passing vehicles in 1×1 (km^2) per unit time (e.g. daily or hourly), for each cell n from the collected raw data from the loop detectors.

2.1. Problem formulation

The objective is to minimize function $E(s)$: $\mathbb{R}^N \to \mathbb{R}$, the daily GHG emissions due to additional travel distance for charging, by determining the optimal density of charging station, $s = \{s_n\}$, $\forall\ n = 1,\ldots N$, as shown in (1) where $E_n(s_n)$: $\mathbb{R} \to \mathbb{R}$. Each s_n represents the density of charging stations in cell n (station/km^2). The GHG emissions per unit distance is represented as e_1 (kg CO_2 e/km), calculated by average level of GHG emissions per unit electricity (kg CO_2 e/kWh) times average electricity consumption per unit travel distance (kWh/km), where "CO_2 e" represents "Carbon dioxide equivalent". The expected deviation distance for each charging request in the nth cell, $d_n(s_n)$: $\mathbb{R} \to \mathbb{R}$ is a function of the decision variable s_n associated with units of km/charging. The annual average daily charging demand in cell n is denoted by W_n (charging/day/cell).

$$\min_{s} E(s) = \min_{s_n,\forall n} \sum_{n=1}^{N} E_n(s_n) = \min_{s_n,\forall n} \sum_{n=1}^{N} [e_1 \cdot d_n(s_n) \cdot W_n] \tag{1}$$

The travel deviation per charging request, $d_n(s_n)$, can be calculated based on the following assumptions; the detailed derivation is presented in Appendix A.

Assumption 1. If a vehicle enters a cell with a certain direction, the final destination is not in the opposite direction.

In Fig. 1, the circle represents a vehicle entering the nth cell from west to east. The destination of the vehicle can be either in the gray Northern area or in the dotted Southern area. This assumption is reasonable in grid networks because drivers do not tend to move in the opposite direction from their destination.

Assumption 2. In a certain cell, stations are uniformly distributed.

Based on this assumption, the average distance between near stations, δ_n (km), is given by (2) (Ahn and Yeo, 2015).

$$\delta_n = s_n^{-\frac{1}{2}} \tag{2}$$

Assumption 3. If a charging request occurs when the charge level reaches a preselected trigger level $\zeta \in (0,1)$, the electric vehicle should go the closest charging station.

Assumption 4. In a cell, vehicles randomly enter the area in any direction but exit the area in any direction except the entering direction. For example, if a vehicle enters a cell from the West, the vehicle does not exit the area across the west bound of the cell.

Assumption 5. In each cell, every station has the same number of chargers, m_n, that is another decision variable, in addition to s_n.

Assumption 6. The additional vehicle-kilometers travelled (VKT) for charging EVs, $d_n(s_n) \cdot W_n$, are much smaller than the total VKT for all vehicles. In other words, q_n and k_n are not influenced by the decision variable s_n.From Appendix A, $d_n(s_n)$ is a function of the decision variable s_n, represented as: