



# Design government incentive schemes for promoting electric taxis in China

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## ARTICLE INFO

### Keywords:

Electric taxis  
Charging behavior  
GPS trajectory data  
Subsidy  
Genetic algorithm

## ABSTRACT

This paper presents an optimization framework to determine the government incentive schemes to promote battery electric vehicle (BEV) taxis. The impacts of drivers' operating behaviors, charger network coverage, BEV range, vehicle costs, and energy prices are taken into account. A two-stage optimization model is proposed, which describes the interplay between the government subsidy scheme and taxi drivers' acceptance of BEVs. To quantify drivers' acceptance, a data-driven microsimulation model is used to simulate driving and charging activities based on GPS trajectory data collected from conventional gasoline taxis in Changsha, China. The optimal government subsidy scheme is solved using the genetic algorithm. The key findings include: (1) detour for charging is inevitable for BEV taxis and would cause significant disruption in operational activities, especially for small-range BEVs (e.g. 150 km). (2) Subsidizing on vehicle purchase is necessary, and the subsidy intensity is expected to maintain at the current level to achieve an electrification goal of more than 50%. The government should provide financial support for public charging exclusive of vehicle purchase. (3) Different taxi drivers might prefer different BEV ranges, thereby they should be allowed to select from diversified BEV models, instead of deploying a single vehicle model for the entire taxi fleet.

## 1. Introduction

Battery electric vehicles (BEVs) can reduce greenhouse gas (GHG) emissions and other harmful pollutants in highly populated urban areas. In particular, deploying BEVs in transit bus and taxi fleets offers passengers a cleaner and quieter ride, saves on fuel costs, and promotes the acceptance of BEVs among the citizens (Tao, 2013). Several electric taxi pilot projects have been deployed around the world, such as in New York City, USA, Tokyo, Japan, Amsterdam, the Netherlands, Jeju, South Korea, and Shenzhen, China (Merkisz-Guranowska and Maciejewski, 2015; Park et al., 2014).

Government incentives, in terms of subsidies and tax credits, have been provided to promote the acceptance of BEVs. Through various forms of incentives, the government can influence the purchase decision of BEVs, the deployment of charging infrastructure, and energy costs. For example, taxi companies in the Amsterdam region, the Netherlands, can receive a total subsidy of €10,000 for purchasing an electric taxi in 2014, including €5000 from the City of Amsterdam and €5000 from the Ministry of Infrastructure and Environment (Netherlands Enterprise Agency, 2015). In Seoul, South Korea, buying electric taxis will be subsidized with up to 50% of the purchase price (ChosunMedia, 2013). In addition to providing purchase incentives for BEVs, the government also faces decisions on how to invest and

incentivize building publicly accessible charging infrastructure. In Germany's three largest cities, namely Hamburg, Munich, and Berlin, the subsidy requirement amounts to €14 million for the expansion of the public charging infrastructure by 2017 (GNPEM, 2015). In Austin, USA, the government provides a rebate of up to \$4000 or 50% of the cost to install approved electric vehicle (EV) Level 2 charging stations and/or Level 1 outlets (AFDC, 2017). The utility companies enact incentive programs that reduce charging costs for residential customers in Austin. For example, with Austin Energy's EV360 program, EV drivers can take advantage of a fixed, time-of-use charging rate as low as \$30/month, which includes unlimited charging at any of the public charging stations enrolled in the program and unlimited off-peak charging at home (Austin Energy, 2017).

Although various incentives have been provided to promote BEV taxis, the effectiveness of these incentives on taxi drivers' acceptance is still unclear. This is a particularly important issue in China, where a large taxi fleet is driven heavily in urban areas, and the government currently provides one of the most aggressive subsidy schemes (Hao et al., 2014; Zhang et al., 2014). China have launched the electric vehicle subsidy scheme since 2009. Taxi companies are eligible for subsidies from the national and municipal governments (MOF, 2009). According to the national policy, the subsidies are ¥1800 per kWh of the battery capacity (MOF, 2015). In some cities, such as Beijing

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(2016), Tianjing (2016) and Changsha (2014), the governments provide a 1:1 match with local subsidies. In addition to subsidizing on BEV purchase, the local governments implement policies to shorten the service life of CGV taxis,<sup>1</sup> and provided subsidies and awards in charging infrastructures (MOF, 2016), whereas no financial incentives are provided for BEV taxi drivers to recover their charging costs.

This study aims at finding the most effective incentive scheme to maximize the adoption of BEV taxis, considering the interplay of government policies and taxi drivers' individual decisions on vehicle choice. In particular, the following research questions are analyzed:

- (1) How would charging activities affect taxi drivers' operational revenue?
- (2) How would BEV taxis compete with CGV taxis when provided with subsidies on vehicle purchase and charging cost?
- (3) How to maximize the adoption of BEV taxis while using the least amount of subsidies?

Research question 1 is addressed by developing a data-driven microsimulation model to estimate the energy-cost revenue and operational losses caused by charging activities. We address research question 2 by comparing the total cost of owning and operating CGVs versus BEVs, taking account of different charger network coverages, BEV ranges, and the combinations of car-buying and charging incentives. Research question 3 is formulated as a two-stage optimization problem and solved using the genetic algorithm.

The remainder of this paper is organized as follows. In Section 2, the review of related work is summarized. Section 3 presents the two-stage optimization framework and the data-driven microsimulation model, followed by the data description of GPS trajectories collected in Changsha, China in Section 4. In Section 5, results and discussions are presented. Section 6 discusses the policy implications regarding the impacts of BEV range, charging infrastructure coverage, vehicle and battery prices, and fuel prices on the adoption of BEV taxis. Section 7 presents concluding remarks.

## 2. Literature review

The prices of electricity and gasoline determine the operational cost and have a significant impact on the acceptance of BEV taxis. According to the sensitivity analysis by Crist (2012) and Ning et al. (2012), low electricity price and high gasoline price made BEV taxis more competitive than CGVs. With the goal of making BEV taxis as profitable as CGV taxis in 5 years, Wang et al. (2015) estimated BEV taxi fares using four types of BEVs with different ranges. The results showed that when the average gasoline price increased to ¥11.47 /L, the BEV taxi fare could be lower than that of CGV taxis; while if the electricity price was set higher than the current residential electricity price, the BEV taxi fare needed to be higher than that of CGVs. To promote electric taxis in Shenzhen, China, Li et al. (2015a) proposed two incentive schemes to reduce BEV taxi drivers' energy cost, namely, reducing the charging tariff and exempting BEV taxi passengers from fuel surcharge tax. Most citizens were happier to take BEV taxis than CGV taxis due to the exemption from fuel surcharge fees. Furthermore, allocating charging infrastructure based on the charging demand help mitigate taxi drivers' range anxiety and promote the market acceptance of BEVs. Sellmair and Hamacher (2014) conducted an event-based simulation of BEV taxis' annual mileage based on the driving patterns of CGV taxis, and proposed an optimization method to find the optimal number of charging stations for the city of Munich, Germany. Based on taxi trajectory

<sup>1</sup> For example, in Beijing, the policy is specifically designed to subsidize BEV adoption in the taxi fleet and shorten the service life of CGV taxis from 8 years to 6 years. If a CGV taxi is retired within 7 years, it can receive a one-off subsidy of ¥10,000 per vehicle, in addition to the national and local government subsidies and the tax exemption on BEV purchase (Beijing, 2015a).

data collected in Beijing, China, Shahraki et al. (2015) and Cai et al. (2014) formulated mathematical models to determine locations of public charging stations that maximize the vehicle-miles-traveled (VMT) of BEV taxis. Their research are intended for assisting the government siting publicly accessible charging infrastructure efficiently and provide insights on allocating charging infrastructure based on the spatial and temporal characteristic of CGV taxis.

The market acceptance of BEV taxis depends on taxi drivers' desires and economic viabilities. A cross-national study conducted by Park et al. (2014) showed regional differences between South Korea and USA in terms of factors influencing the adoption of BEV taxis. Price-related factors are cited as the biggest obstacles for taxi drivers' acceptance of BEVs in South Korea; while in USA, drivers are more concerned about societal responsibilities. The ownership cost is widely used to assess the cost effectiveness of BEVs. The key elements of ownership costs include vehicle price, purchase tax, registration and license fee, fuel cost, and operation and maintenance (O&M) cost (Crist, 2012; Delucchi and Lipman, 2001; Egbue and Long, 2012; Hao et al., 2014; Neubauer et al., 2012; Trip and Konings, 2014; Wang and Li, 2013). By monitoring eight electric vehicles with battery ranges of 175 km and 130 km, operated either as part of a local taxi fleet or as a service vehicle for local authorities in the Netherlands, Baert and Kort (2013) found that BEVs were economically viable with current subsidies—3% of purchase cost reduction and 36% of purchase cost tax deduction. The results of economic evaluation of BEV taxis in Singapore indicated that BEV taxis could be economically viable considering their eight-year lifetime, however, the battery replacements, the high purchase price, and the leasing rates of BEV taxis could hinder public acceptance (Kochhan and Sellmair, 2016).

Overall, technical, economic, behavioral and regulatory parameters have significant impacts on the market acceptance of BEV taxis. The effectiveness of incentives depends on how taxi drivers react to the policies. Since it is common for taxis to install GPS devices for the purpose of navigation and operational monitoring, taxi trajectories become a major data source to examine to drivers' behaviors and operational characteristics. Due to the shortage of the real-world BEV trajectory data, the data collected from CGVs, representing real world travel activities, have been used to assess BEV market potential (Chrysostomou et al., 2016; Wang et al., 2015; Yang et al., 2016) and optimize the siting of public charging stations (Cai et al., 2014; Tu et al., 2016; Yang et al., 2017). Some pioneering works using BEV taxi trajectory data reveal taxi drivers' charging patterns (Li et al., 2015b; Zou et al., 2016), and provide key parameters to simulate charging behavior of BEV taxis. To our knowledge, no prior research has been done to design government incentive schemes taking into account of taxi driving and charging activities. This paper presents a data-driven microsimulation approach to examine taxi drivers' individual decisions on vehicle choice, considering the impacts of government incentives, charger network coverage, BEV range, vehicle and battery costs, and energy prices. The government incentive scheme is optimized using the simulation model.

## 3. Methods

### 3.1. Two-stage optimization framework

A two-stage iterative process is designed to find the optimal incentive scheme. At Stage 1, the government determines a set of incentives with a certain goal, for example, subsidizing vehicle purchase and charging cost in order to achieve a taxi electrification rate of  $w_0$  (in %), that is, more than  $w_0$  of CGV taxis would be replaced by BEVs. At Stage 2, taxi drivers will compare the total cost of owning and operating CGVs versus BEVs, taking into account the incentives, and decide whether to switch to BEVs or not. In particular, the gross profit (GP) (in ¥1000), defined as the cost for owning and operating a BEV taxi minus the costs of a CGV taxi, is estimated. If the gross profit is positive, the taxi driver will switch to a BEV. If the collective effect of taxi drivers' vehicle choices does not achieve the taxi electrification goal, the incentive scheme is adjusted in Stage 1.

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