Optimal Intervention for Incentivizing the Adoption of Commercial Electric Vehicles

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***Abstract*—While electric vehicles (EVs) have great potential in reducing greenhouse gas emissions, successful EV adoption depends largely on the availability of public charging stations. The lack of charging stations poses an even more serious problem for the adoption of *commercial* EVs (e.g., trucks used for freight transportation), because the (commercial EV) fleet planner needs to build their own specialized charging stations, requiring additional investment in commercial EV purchase. This paper presents a first mathematical model and rigorous analysis for incentivizing the adoption of commercial EVs. We propose an intervention policy for the social planner (e.g., the government) to promote commercial EV adoption. The intervention policy includes a subsidy for EV purchase (i.e., expenditure) and a carbon tax for gas emissions (i.e., income). We propose provably fast algorithms for the social planner to find the optimal budget-balanced intervention policy. We analyze in detail the effect of the intervention policy on commercial EV adoption, and prove that the proposed intervention policy achieves higher commercial EV adoption rates.**

I. Introduction

According to the latest report by U.S. Environmental Protection Agency (EPA) [1], transportation contributed to 28% of total U.S. greenhouse gas (GHG) emissions in 2012. A promising solution for reducing GHG emissions is to replace traditional gas vehicles (GVs) with zero-emission electric vehicles (EVs). However, despite the great efforts in promoting the EV adoption, the market share of EVs in the new vehicle market remains at an extremely low level (about 0.73% as reported in [2]).

One hurdle for EV adoption may be the lack of public infrastructure for EV charging. In [3], it is shown that in the case of residential EV adoption, the profit-seeking investors (e.g., vendors of charging stations, car companies) tend to underinvest in building EV charging stations, compared to the socially optimal investment level. This underinvestment in EV charging stations negatively affects the consumers' decisions towards purchasing EVs.

While most research has focused on *residential* EVs, it is equally important to study the adoption of EVs in *commercial* fleets, which are used in airport transportation and supply chains owned by large companies (e.g., Walmart, Amazon, and so on). The lack of EV charging stations poses an even more serious problem in commercial EV adoption. This is because the vehicles used in commercial fleets are usually heavy-duty vans and trucks with shorter driving ranges and longer distances to destinations, and require more expensive charging stations with higher capacity on the road. Hence, the fleet owners may need to upgrade existing or even build new charging stations for their special needs. This additional investment on charging stations by the EV buyers (which, in this case, are the fleet owners) makes the adoption of commercial EVs even harder.

A. Our Contribution

To the best of our knowledge, our work presents the first mathematical modeling and rigorous analysis of *commercial* EV adoption.

We model the commercial EV adoption as a game between a social planner (e.g., the government) and a fleet planner (i.e., the owner of the fleet). The social planner aims to maximize the social welfare (e.g., the percentage of EVs in the fleet, or the percentage of mileages traveled by EVs in the total mileages). It can improve the social welfare by an *intervention policy*, which consists of subsidizing the initial purchase of EVs and collecting a carbon tax for GHG emissions from GVs. The social planner needs to achieve this goal while maintaining a balanced budget (i.e., the expenditure on subsidy is equal to the income from the carbon tax). The social planner's decision problem is challenging due to the budget balance constraint. On one hand, the social planner cannot subsidize too little to promote the EV adoption. On the other hand, the social planner cannot subsidize so much that the fleet planner does not purchase GVs at all, in which case the social planner cannot collect any carbon tax to offset its expenditure.

The fleet planner needs to move a certain amount of freight from a source to a destination through several possible routes. It determines the numbers of EVs and GVs to purchase, and allocates the EVs and GVs in each possible route. The fleet planner aims to make the optimal decisions to minimize her total cost while shipping all the freight. The total cost of the fleet planner includes the cost (initial purchase and every-day maintenance) of vehicles, the cost of building charging stations on each route, and the cost of the carbon tax. Compared to residential consumers, the fleet planner is faced with a more challenging decision problem, due to the additional operational decision (i.e., allocation of vehicles on each route) and its coupling with the initial purchase decision.

Our major contributions are as follows. First, we propose algorithms for the fleet planner to make optimal fleet management decisions and for the social planner to find the optimal budget-balanced intervention policy. Both algorithms converge provably fast (i.e., in logarithmic time).

Second, we rigorously analyze the effect of the proposed intervention policy. Our main finding is that the intervention policy promotes commercial EV adoption, even when compared to the case where the fleet planner does not need to build charging stations but the social planner does not intervene. Therefore, we prove the value of the proposed intervention policy in commercial EV adoption: it overcomes the additional challenge that the EV buyers (i.e., the fleet planner) need to invest on building charging stations.

B. Related Works

1) Residential EVs: Most existing works on residential EVs study the optimal EV charging strategies, *given* that the charging stations have been built and that the EVs have been purchased [4][5][6]. There are also works that study the optimal deployment of public charging stations, again *given* that the EVs have been purchased [7].

The analysis of residential EV adoption, which focuses on the interplay between building charging stations and purchasing EVs, was very recently studied in [3]. However, in residential EV adoption [3], the consumers do not invest on the charging stations and do not make decisions on vehicle allocation.

2) Commercial EVs: Most works on commercial EV adoption are empirical or simulation-based [8]. In contrast, our work builds agent-based models for the fleet planner and the government, and mathematically analyzes their decisions and the impact of the intervention policy on the EV adoption.

II. Model

Consider a freight transportation system with a fleet planner and a social planner. The fleet planner optimizes its decisions on vehicle purchase and route selection in order to minimize its operational cost. The social planner aims to incentivize the fleet planner to purchase and use more electric vehicles. Next, we describe the fleet planner and the social planner in detail.

A. The Fleet Planner

The fleet planner has the amount $F \in \mathbb{R}_+$ of freight to transport from one source to one destination. There are $R \in \mathbb{N}_+$ possible routes. The fleet planner needs to decide the numbers of electric vehicles on each route, denoted by a vector $\boldsymbol{m}_e = (m_{e,1}, \ldots, m_{e,R}) \in \mathbb{R}_+^R$, and the numbers $\boldsymbol{m}_g = (m_{g,1}, \ldots, m_{g,R}) \in \mathbb{R}_+^R$ of gas vehicles on each route. Note that we should think of $m_{e,r}$ and $m_{g,r}$ as the number of vehicles normalized by the full load capacity. Hence, we allow $m_{e,r}$ and $m_{g,r}$ to be non-integers when some vehicles are not fully loaded. For example, $m_{e,r} = 1.4$ means that there are one fully-loaded EV and a 40%-loaded EV on route r. Assuming that the full load of a EV and a GV are f_e and f_g, the fleet planner needs to ensure that all the freight is delivered, namely $f_e \cdot \sum_r m_{e,r} + f_g \cdot \sum_r m_{g,r} \geq F$.

The average cost of the fleet includes the initial purchase cost and the every-day operational cost of the vehicles among other costs that will be described later (such as the cost/subsidies imposed by the social planner). Assuming that time is slotted at $0, 1, 2, \ldots$ and that the fleet planner discounts future costs by $\delta \in [0, 1)$, the average cost of an EV is

$$\begin{aligned} p_e(\delta) &= (1-\delta) \cdot \left[(\text{purchase}) + \sum_{n=1}^{\infty} \delta^n \cdot (\text{operational}) \right] \\ &= (1-\delta) \cdot (\text{purchase}) + \delta \cdot (\text{operational}). \end{aligned} \tag{1}$$

Similarly, we can write the average cost of a GV as $p_g(\delta)$.

Since the EVs in the fleet are heavy-duty vehicles, the residential charging stations do not have enough capacity. As a result, the fleet planner needs to build new charging stations (or upgrade existing ones) before the fleet operates. The cost of building charging stations on route r depends on the number and the capacity of the charging stations, which are ultimately determined by the route (i.e., its length) and the number of EVs allocated to this route. Hence, we write the cost of building charging stations on route r as $c_r(m_{e,r})$. We assume that c_r is strictly increasing, strictly convex, and satisfies $c_r(0) = 0$, and write the set of all such c_r as $\mathcal{C}$.

B. The Social Planner

The social planner subsidizes the initial purchase of a EV by $q_e \geq 0$ per EV. It also charges an every-day carbon tax for GVs running on route r. The carbon tax, written as $t_{g,r}(m_{g,r})$, is a function of the number of gas vehicles. It also depends on the route, because the social planner may want to reduce GHG emissions more on some routes that go through heavily-populated residential areas. The social planner requires the carbon tax to be convex, in order to discourage excessive emission.

We call the collection of the EV subsidy q_e and the carbon tax $t_{g,r}(\cdot)$ *the intervention policy*. The social planner needs to design an intervention policy that balances the budget (i.e., the expenditure of the EV subsidy is equal to the collected carbon tax), and that incentivizes the fleet planner to purchase more EVs.

C. Problem Formulation

1) The Fleet Planner's Fleet Management Problem: The fleet planner's goal is to minimize the average cost by determining the numbers of electric and gas vehicles on each route, subject to the constraint of delivering all the freight. We formulate the fleet planner's decision problem FP as follows:[1]

$$\texttt{FP}:$$

$$\min_{\boldsymbol{m}_e,\boldsymbol{m}_g} \underbrace{\sum_r \left[p_{e,r}(\delta)-(1-\delta)q_e\right]\cdot m_{e,r}}_{\text{cost of electric vehicles}} \tag{2}$$

$$+\underbrace{(1-\delta)\cdot\sum_r c_r(m_{e,r})}_{\text{cost of charging stations}}$$

$$+\underbrace{\sum_r p_{g,r}(\delta)\cdot m_{g,r}}_{\text{cost of gas vehicles}}+\underbrace{\delta\cdot\sum_r t_{g,r}(m_{g,r})}_{\text{cost of carbon tax}}$$

$$s.t.\quad f_e\cdot\sum_r m_{e,r}+f_g\cdot\sum_r m_{g,r}\ge F, \tag{3}$$

$$m_{e,r}\ge 0,\ m_{g,r}\ge 0. \tag{4}$$

We write the solution to the fleet planner's problem FP as $\boldsymbol{m}_e^*(q_e,\boldsymbol{t}_g)$ and $\boldsymbol{m}_g^*(q_e,\boldsymbol{t}_g)$. Note that the optimal allocation of electric and gas vehicles on each route is a function of the social planner's intervention functions q_e and $\boldsymbol{t}_g$.

2) The Social Planner's Intervention Policy Design Problem: The social planner's goal is to maximize the social welfare by choosing the intervention policy (i.e., the amount of subsidy for purchasing an EV and the carbon tax), subject to the budget balance constraint. We define the social welfare as a function of the numbers of electric and gas vehicles, denoted by $W(\boldsymbol{m}_e,\boldsymbol{m}_g)$. It should be increasing in each $m_{e,r}$ and decreasing in each $m_{g,r}$. Examples could be the percentage of electric vehicles in the fleet, or the percentage of mileages traveled by electric vehicles. We formulate the social planner's decision problem SP as follows:

$$\texttt{SP}:$$

$$\max_{q_e,\boldsymbol{t}_g}\ W\left(\boldsymbol{m}_e^*(q_e,\boldsymbol{t}_g),\boldsymbol{m}_g^*(q_e,\boldsymbol{t}_g)\right) \tag{5}$$

$$s.t.\quad q_e\cdot\sum_r m_{e,r}^*(q_e,\boldsymbol{t}_g)=\sum_r t_{g,r}\left(m_{g,r}^*(q_e,\boldsymbol{t}_g)\right), \tag{6}$$

$$q_e\ge 0,\ t_{g,r}\ \text{positive and increasing}. \tag{7}$$

III. Optimal Fleet Planning and Intervention

We propose algorithms for the fleet planner to optimize its fleet management and for the social planner to find the optimal budget-balanced intervention policy. Both algorithms converge fast (i.e., linearly) in algorithmic time.[2]

Theorem 1: The fleet planner's fleet management algorithm in Table I converges linearly with rate 0.5 to the optimal solution to FP in logarithmic time.[3]

[1]The objective (2) in FP is approximate, because the actual costs of electric vehicles and gas vehicles should be $\sum_r[p_{e,r}(\delta)-(1-\delta)q_e]\cdot\lceil m_{e,r}\rceil$ and $\sum_r p_{g,r}(\delta)\cdot\lceil m_{g,r}\rceil$, respectively (namely, we need to buy an integer number of vehicles). However, the approximate cost of vehicles is within $\max\{p_{e,r}(\delta)-(1-\delta)q_e,p_{g,r}(\delta)\}\cdot R$ of the actual cost. The difference is negligible when the number R of routes is much smaller than the number ($\ge\frac{F}{\max\{f_e,f_g\}}$) of vehicles required, which is usually the case. Hence, we use the approximate cost as the objective to make FP tractable.

[2]We say a sequence $x_1,x_2,\ldots$ converges linearly with rate ρ to x^*, if $\frac{\|x_{k+1}-x^*\|}{\|x_k-x^*\|}\le\rho$. [9, Sec. 9.3.1]

[3]Due to space limitation, all the proofs are in our online appendix [10].

TABLE I
Algorithm for Optimal Fleet Management.

Initialization: $\underline{\lambda}=0$, $\lambda=1$, $\bar{\lambda}=\lambda$

```
% route selection given λ:
```
for $r=1,\ldots,R$

$$m_{e,r}=\begin{cases}0 & \text{if } p_e(\delta)-(1-\delta)q_e+(1-\delta)c_r'(0)\ge\lambda f_e\\ (c_r')^{-1}\left(\frac{\lambda f_e-p_e(\delta)}{1-\delta}+q_e\right) & \text{otherwise}\end{cases}$$

$$m_{g,r}=\begin{cases}0 & \text{if } p_g(\delta)+\delta\cdot t_{g,r}'(0)\ge\lambda f_g\\ (t_{g,r}')^{-1}\left(\frac{\lambda f_g-p_g(\delta)}{\delta}\right) & \text{otherwise}\end{cases}$$

end for

```
% find the range of λ:
```
while $f_e\cdot\sum_r m_{e,r}+f_g\cdot\sum_r m_{g,r}<F$
  $\lambda\leftarrow 2\cdot\lambda$, $\bar{\lambda}=\lambda$
  route selection given λ
end while
$\lambda=(\underline{\lambda}+\bar{\lambda})/2$, route selection given λ

```
% bisection method to find the optimal λ:
```
while $\bar{\lambda}-\underline{\lambda}>$ given precision
  if $f_e\cdot\sum_r m_{e,r}+f_g\cdot\sum_r m_{g,r}<F$
    $\underline{\lambda}=\lambda$
  else
    $\bar{\lambda}=\lambda$
  end if
  $\lambda=(\underline{\lambda}+\bar{\lambda})/2$, route selection given λ
end while

The social planner chooses the optimal intervention policy from the policy space. Since the policy includes the carbon tax function, the policy space is infinite-dimensional. For tractability, we restrict to parametrized intervention policies. In particular, we focus on linear carbon tax where $t_{g,r}(m_{g,r})=t_{g,r}\cdot m_{g,r}$. Then we have the following theorem.

Theorem 2: The social planner's intervention policy design algorithm in Table II converges linearly with rate 0.5 to the optimal solution to SP (restricted to linear carbon tax) in logarithmic time.

IV. Analysis of Electric Vehicle Adoption

In this section, we analyze in detail the effect of the proposed intervention policy on the EV adoption.

A. Impact on the Social Welfare

Since the social welfare $W(\boldsymbol{m}_e,\boldsymbol{m}_g)$ (e.g., the percentage of electric vehicles in the fleet, or the percentage of EV mileages) is increasing in $m_{e,r}$ and decreasing in $m_{g,r}$, it serves as a good measure for the status of EV adoption.

Not surprisingly, our proposed intervention policy always improves or maintains the social welfare, compared to that under no intervention policy, and hence promotes the EV adoption. This is simply because the proposed intervention policy reduces the cost of EVs and charges the carbon tax for using gas vehicles. Importantly, the proposed intervention policy promotes the EV adoption while maintaining a balanced budget.

TABLE II

ALGORITHM TO FIND THE OPTIMAL INTERVENTION POLICY.

Initialization: $\underline{q}_e = 0$, $q_e = 10^{-3}$, $\bar{q}_e = p_e$

```
% find the range of q_e:
while q_e · Σ_r m_{e,r} < Σ_r q_{g,r} · m_{g,r}
    q_e ← 2 · q_e, q̄_e = q_e
    find m_{e,r} and m_{g,r} using the algorithm in Table I
end while
λ = (λ_ + λ̄)/2, find m_{e,r} and m_{g,r} using Table I
% bisection method to find the optimal q_e:
while q̄_e − q_e > given precision
    if q_e · Σ_r m_{e,r} < Σ_r q_{g,r} · m_{g,r}
        q_e_ = q_e
    else
        q̄_e = q_e
    end if
    q_e = (q_e_ + q̄_e)/2, find m_{e,r} and m_{g,r} using Table I
end while
```

Proposition 1: Our proposed intervention policy always improves or maintains the social welfare, compared to that under no intervention policy, namely

$$W\left(\boldsymbol{m}_e^*(q_e^*, \boldsymbol{t}_g^*), \boldsymbol{m}_g^*(q_e^*, \boldsymbol{t}_g^*)\right) \geq W\left(\boldsymbol{m}_e^*(q_e = 0, \boldsymbol{t}_g \equiv 0), \boldsymbol{m}_g^*(q_e = 0, \boldsymbol{t}_g \equiv 0)\right).$$

Now imagine a scenario where there is *no cost* in building the charging stations (entities other than the fleet planner build them or subsidize all the cost). The absence of the cost in charging stations would make it easier to adopt EVs. We compare this imaginary scenario with no cost in building charging stations and with no intervention, with the considered scenario with costs and with the proposed intervention policy. We can prove that the number of EVs purchased in the latter scenario is always no smaller than and sometimes strictly larger than that in the former scenario. This shows the great value of intervention: it overcomes the special hurdle in commercial EV adoption that the buyers need to build charging stations. We summarize the above discussion in the following theorem.

Since there are costs of charging stations involved, we write the fleet planner's optimal decision as $\boldsymbol{m}_e^*(q_e, \boldsymbol{t}_g, c_r)$ and $\boldsymbol{m}_g^*(q_e, \boldsymbol{t}_g, c_r)$.

Theorem 3: For any cost $c_r \in \mathcal{C}$, we have

$$W\left(\boldsymbol{m}_e^*(q_e^*, \boldsymbol{t}_g^*, c_r), \boldsymbol{m}_g^*(q_e^*, \boldsymbol{t}_g^*, c_r)\right) \geq W\left(\boldsymbol{m}_e^*(q_e = 0, \boldsymbol{t}_g \equiv 0, c_r' \equiv 0), \boldsymbol{m}_g^*(q_e = 0, \boldsymbol{t}_g \equiv 0, c_r' \equiv 0)\right).$$

In particular, when $p_e(\delta) > p_g(\delta)$, we have

$$W\left(\boldsymbol{m}_e^*(q_e^*, \boldsymbol{t}_g^*, c_r), \boldsymbol{m}_g^*(q_e^*, \boldsymbol{t}_g^*, c_r)\right) > W\left(\boldsymbol{m}_e^*(q_e = 0, \boldsymbol{t}_g \equiv 0, c_r' \equiv 0), \boldsymbol{m}_g^*(q_e = 0, \boldsymbol{t}_g \equiv 0, c_r' \equiv 0)\right).$$

B. Emission Control

The social planner can control the numbers of GVs on each route through the carbon tax. It can reduce the numbers of GVs on route r by imposing a large $t_{g,r}$. To obtain sharp results on the GHG emissions on each route, we focus on linear carbon tax $t_{g,r}(m_{g,r}) = q_{g,r} \cdot m_{g,r}$. The following theorem proves that the social planner can control the GHG emission on different routes by setting $q_{g,r}$ properly.

Theorem 4: Under linear carbon tax, the gas vehicles only travel on routes with the smallest $p_{g,r}(\delta) + \delta \cdot t_{g,r}$, namely

$$m_{g,r}^* \begin{cases} > 0, & r \in \arg\min_{r'} \{p_{g,r'}(\delta) + \delta \cdot q_{g,r'}\} \\ = 0, & \text{otherwise} \end{cases}.$$

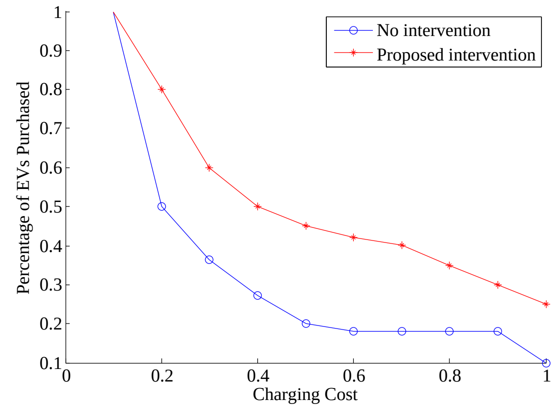

Fig. 1. Percentage of EVs purchased versus the cost of charging stations.

V. SIMULATION RESULTS

We consider the following simple, yet representative scenario. A fleet planner with $\delta = 0.5$ has freight that can be transported with 10 vehicles (EVs and GVs have the same full-load capacity). The average cost of a EV is normalized to $p_e(\delta) = 1$ and that of a GV is $p_g(\delta) = 2$. There is only one route. The cost of building charging stations is $c_1 = c \cdot m_{e,r}^2$. We change the coefficient in the cost function as $c = 0, 0.1, 0.2, \ldots, 1.0$. In Fig. V, we show the percentages of EVs purchases with no intervention and with the proposed intervention policy. We can see that the proposed intervention policy greatly improves the EV adoption, especially when the cost of charging stations is high.

VI. CONCLUDING REMARKS

This work builds the first analytical model for commercial EV adoption. We study a fleet planner's decision on EV adoption, which is influenced by its operational decisions of route selection and vehicle allocation, as well as by the social planner's intervention policy. We propose fast algorithms to find the optimal fleet management decision and the optimal budget-balanced intervention policy. Our main result is that the proposed intervention policy promotes commercial EV adoption, overcoming the additional investment in charging stations by the fleet planner.

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