Managing Bottleneck Congestion through Incentives on Electric Vehicle Charging and Lane Segmentation

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SHORT SUMMARY

An incentive-based traffic demand management policy is proposed to alleviate traffic congestion on a road stretch that creates a bottleneck for the commuters. The incentive targets electric vehicles owners by proposing a discount on the energy price they use to charge their vehicles if they are flexible in their departure time. We propose dedicated lanes for electric vehicles to further reduce traffic congestion and to promote the usage of electric vehicles over fossil-fueled vehicles. We theoretically show the optimal road segmentation and compare this to scenarios with and without incentive-based electric vehicle charging. We support our theoretical findings with numerical simulations that allow us to highlight the power of the proposed methods and to provide practical advice for the design of policies.

Keywords: Bottleneck Congestion, Electric Vehicle Charging, Incentive-Based Traffic Demand Management, Lane Segmentation, Dedicated Lanes

1. INTRODUCTION

Road traffic is known to be a major source of fuel consumption and a concern for pollution and climate change. The increasing number of road users has lead to an increase in road congestion over the years, and as a consequence the concentrations of several pollutants are expected to nearly double during the rush hour in modern cities (Zhang et al., 2011). The fast share of Plug-in Electric Vehicles (PEVs) is also negatively affected by congestion. According to Bingham et al. (2012), they experience a higher battery consumption during congested rush hours.

Highly congested periods are usually associated with commuting times during the morning and evening. The bottleneck model has been developed to capture situations in which commuters face one main source of road congestion during their travel. Arguably, the most relevant application can be found in the modelling of a highway that connects origins to destinations (Vickrey, 1969). The structural model explicitly incorporates physical aspects of the road congestion as well as behavioural decisions of drivers. Individual commuters select their departure time as a best response to their local travelling cost that depends on the departure time chosen by the others. Due to this selfish inclination of the drivers, the road capacity can be saturated leading to congestion (Arnott et al., 1990, 1993; R. Lindsey, 2004; Small, 2015). We refer to Li et al. (2020) and references therein for a recent overview on applications and findings regarding the bottleneck model.

In the literature, various solutions have been proposed to reduce bottleneck congestion. On the one hand, there are policies that enforce a price on the use of the bottleneck segment, e.g., tolling (Van den Berg & Verhoef, 2011; C. R. Lindsey et al., 2012). Such policies are known as *hard policies* as the users are forced to comply. On the other hand, there are *soft policies*, also known as Incentive Based Traffic Demand Management (IBTDM), where commuters are rewarded if they enter the bottleneck outside the peak of congestion (Sun et al., 2020). Whereas policies such as tolling have been extensively studied, positive incentives have received considerably less attention, despite the fact that they can have higher acceptability from the commuters and improve fairness.

We build on the work of Cenedese et al. (2021), who propose an incentive-based electric vehicle charging policy. This work show that a dynamically discounted energy price is an effective policy to decrease congestion during rush hours if the full population drives electric. We extend to more realistic settings where a part of the population drives electric vehicles and another part drives fossil-fueled vehicles. We study the effect of road segmentation, where separate lanes are dedicated to electric vehicles. A road segmentation policy where certain types of vehicles are prioritized has been applied to High Occupancy Vehicle (HOV) lanes (Cassidy et al., 2010; Lamotte et al., 2021), High Occupancy/Toll (HOT) lanes (Lou et al., 2011) and lanes dedicated to connected vehicles (Xiao et al., 2019), but to the best of the authors knowledge has not been previously applied to PEVs.

2. METHODOLOGY

Classical Bottleneck Model

We briefly review the classical bottleneck model that is the foundation of our analysis. The discussion follows Arnott et al. (1987). The model comprises $N \in \mathcal{N}$ commuters (or agents) who travel from their origin, e.g., home, to their destination, e.g., work. During their trip, they pass through a single bottleneck, that is assumed to be the only potential source of congestion they may encounter. The capacity of the road at the bottleneck is assumed to be constant and equal to $s > 0$ vehicles per time instant. If the departure rate $r(t) : \mathbb{R}_+ \to \mathbb{R}_+$ at which the vehicles enter the bottleneck is greater than s, for some time instant t, then a queue $Q(t) : \mathbb{R}_+ \to \mathbb{R}_+$ is created. The queue dynamics read

$$Q(t) = \int_{\hat{t}}^{t} r(\tau)\,\mathrm{d}\tau - s(t - \hat{t}), \tag{1}$$

where $\hat{t} < t$ is the last moment at which there was no congestion, i.e., $Q(\hat{t}) = 0$. The vehicles leave the queue according to a First-In-First-Out (FIFO) principle. For each agent $i \in \{1, \ldots, N\} = \mathcal{N}$ arriving at the bottleneck at time t, the complete travel time experienced is

$$T_i(t) = T_i^{\mathrm{f}} + T^{\mathrm{v}}(t), \tag{2}$$

where $T_i^{\mathrm{f}} \geq 0$ denotes the fixed time it takes agent i to commute in the absence of traffic congestion. The time T_i^{f} can differ between agents, but does not play a role in the agents' decision-making process, so without loss of generality we assume that $T_i^{\mathrm{f}} = 0$ for all $i \in \mathcal{N}$, as done in Arnott et al. (1987). $T^{\mathrm{v}}(t) \geq 0$ is the additional time spent due to the traffic congestion. Clearly, $T^{\mathrm{v}}(t) > 0$ if and only if $Q(t) > 0$ and depends only on the time at which the vehicles enter the bottleneck. The waiting time at the bottleneck is

$$T^{\mathrm{v}}(t) = \frac{Q(t)}{s}. \tag{3}$$

Therefore, if we denote by t^* the common desired arrival time of the commuter, as in Arnott et al. (1987), the time $0 \leq t' \leq t^* \leq N/s$ at which it has to enter the bottleneck to reach its destination at t^* is

$$t' + T^{\mathrm{v}}(t') = t^*. \tag{4}$$

The agents are assumed to be perfectly rational, that is, they select the t that minimises their own "cost". The cost of an agent is associated to the discomfort experienced by choosing a particular departure time. If a commuter leaves at $t < t'$ or $t > t'$, then it will arrive early or late, respectively. The cost per unit of time of arriving early is $\beta > 0$, that of being late is $\gamma > 0$, while time spent in congestion is penalized by $\alpha > 0$ (Vickrey, 1969; Arnott et al., 1987). As shown in Arnott et al. (1987); van den Berg & Verhoef (2011), one should select $\beta < \alpha < \gamma$ to avoid unnatural user behaviour. In equilibrium, the generalized cost of every individual, which we denote by ϕ_N, is

$$\phi_N = \beta t^* = \beta \frac{\gamma N}{s(\beta + \gamma)}. \tag{5}$$

Incentive-Based Electric Vehicle Charging

Cenedese et al. (2021) extend the classical bottleneck model by considering the presence of PEVs that receive an incentive if they do not travel during congested periods. The incentive is a discount $p(t) : \mathbb{R}_+ \to \mathbb{R}_+$ over the price of the electricity purchased by the owner. Here, $p(t)$ depends on the time at which the PEV enters the bottleneck, rather than the time at which it starts charging. We assume that each PEV must charge for $\bar{\delta} > 0$ time instants before entering the bottleneck. They can choose to charge at home, at a fixed energy price $\bar{p}$, or, at one of the charging stations that take part in the policy at a variable energy price $\bar{p} - p(t)$. The charging station can be located anywhere along the path that the commuter takes to reach the bottleneck. This addition endows the PEV commuting with an additional degree of freedom. In fact, they now have two decision variables: 1) the time at which they enter the bottleneck t, 2) the time spent at the charging station $\delta \in [0, \bar{\delta}]$.

Following from the results of Sun et al. (2020) and Cenedese et al. (2021), when a total budget of M is available for incentives and these incentives are distributed in order to minimize congestion, the generalized costs of electric vehicles (ϕ_E) is given as follows, where t^l is the time at which congestion starts

$$\phi_E = \beta(t^* - t^l) = \beta \left[\frac{\gamma N}{s(\beta + \gamma)} - \sqrt{\frac{2\gamma M}{s\beta(\beta + \gamma)}} \right]. \tag{6}$$

Dedicated Lanes for Electric Vehicles

When the population of road users is a mixed set of electric and non-electric vehicles, the generalized cost functions ϕ_N and ϕ_E can differ across the population, as only a part of the population can benefit from the incentives on electricity charging. In the absence of dedicated lanes, this can be modelled through a penetration rate for which the reader is referred to Sun et al. (2020).

In this work, we assume the road can be segmented in two types of lanes. General use lanes (denoted with subscript R) which can be used by any vehicle and lanes that are solely devoted to electric vehicles, referred to as dedicated or electric lanes (denoted with subscript E). Although PEVs have full freedom in choosing the lane and whether to charge or not, the charging incentives are only available for vehicles travelling on the dedicated lanes. The total number of regular (non-electric) and electric vehicles is equal to $\hat{N}_R$ and $\hat{N}_E$ respectively. The number of vehicles on general use or electric lanes is denoted by N_R and N_E respectively, for which it holds that $N_R + N_E = \hat{N}_R + \hat{N}_E$, $N_R \geq \hat{N}_R$ and $N_E \leq \hat{N}_E$. The total road capacity (i.e. number of lanes) is equal to s and the capacity attributed to general use and electric lanes is denoted by s_R and s_E respectively. We aim to determine the optimal distribution of capacity among the two types of lanes. We note that this can be reduced to a single decision variable s_E, as the value for $s_R = s - s_E$. A graphical representation is given in Figure 1, where red cars are non-electric vehicles, blue cars are electric vehicles and a yellow charging symbol signals that an electric vehicle has used the charging station and received an incentive.

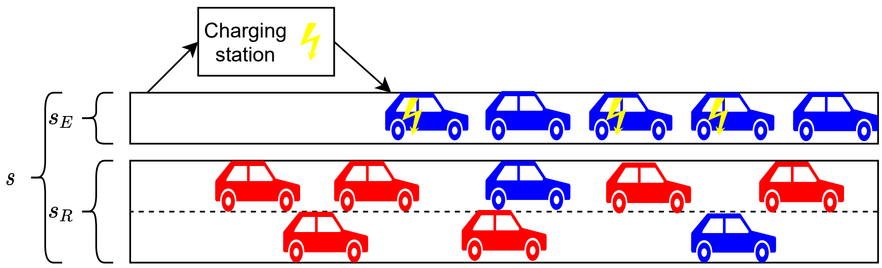

Figure 1: Graphical representation of lane segmentation with a charging station with $N_R = 8$, $N_E = 5$, $\hat{N}_R = 6$ (red) and $\hat{N}_E = 7$ (blue)

As defined before, ϕ_R is the generalized cost of an individual travelling on a general use lane and ϕ_E is the generalized cost of an individual travelling on the dedicated lanes.

$$\phi_R = \beta t^* \qquad = \beta \frac{\gamma N_R}{s_R(\beta+\gamma)} = \beta \frac{\gamma N_R}{(s-s_E)(\beta+\gamma)}. \tag{7}$$

$$\phi_E = \beta(t^* - t^l) \qquad = \beta \left[\frac{\gamma N_E}{s_E(\beta+\gamma)} - \sqrt{\frac{2\gamma M}{s_E \beta(\beta+\gamma)}} \right]. \tag{8}$$

Due to the free choice of PEVs for either of the two lanes, it follows that in equilibrium $\phi_E \leq \phi_R$. Intuitively, an electric vehicle will always choose the lane with the lowest cost. A regular vehicle, however, always has to take the general use lane. In equilibrium, the number of vehicles on the electric lane are defined as follows, which can be obtained by equating Equation (7) and (8).

$$N_E = \begin{cases} \hat{N}_E & \text{if } \phi_E < \phi_R, \\ \min(\hat{N}_E, \frac{s_E}{s} N + \frac{s-s_E}{s} \sqrt{\frac{2M(\beta+\gamma)s_E}{\beta\gamma}} & \text{if } \phi_E = \phi_R. \end{cases} \tag{9}$$

If in equilibrium the generalized cost on an electric lane is lower than the cost on a general use lane, this implies that all PEVs will be on the dedicated lanes to minimize their costs. If they are equal, PEVs can be distributed over the two lanes. The number of PEVs that make use of the charging station and the corresponding incentives is an optimal decision for every individual given the number of vehicles, the budget M and the maximum charging time $\bar{\delta}$. For this, the reader is referred to Cenedese et al. (2021).

The number of lanes is determined in such a way that it minimizes the cost experienced by the total number of road users. The cost function reads

$$TC = N_R \phi_R + N_E \phi_E. \tag{10}$$

Without incentives, that is, for a budget $M = 0$, it is clear that $\phi_R(N_r, s_R) = \phi_E(N_E, s_e)$, following from Equations (7) and (8). In this case, as PEVs can use both roads, the optimal number of roads dedicated to PEVs is between between 0 and $s\frac{\hat{N}_E}{\hat{N}_E+\hat{N}_R}$. This is formalized in Theorem 1, which is presented without a proof, given the space limitation.

Theorem 1. *Without incentives (i.e. for a budget $M = 0$), the optimal road capacity $s_E^* \in [0, s\frac{\hat{N}_E}{\hat{N}_E+\hat{N}_R}]$.*

For a budget $0 < M < \infty$, incentives are offered to either all or a selection of PEVs on the dedicated lanes, reducing their generalized costs. Lemma 1 describes two important properties of the relation between road capacity and the number of vehicles on each lane, when the budget is non-zero.

Lemma 1. *For a budget $0 < M < \infty$,*

1. *N_E is non-decreasing in s_E, i.e. $\frac{\partial N_E}{\partial s_E} \geq 0$.*
2. *Given the optimal road capacity s_E^*, $N_E = \hat{N}_E$ and $N_R = \hat{N}_R$.*

Proof. To prove that N_E is non-decreasing in s_E, we consider the two cases $N_E = \hat{N}_E$ and $N_E < \hat{N}_E$ separately. For the case where $N_E = \hat{N}_E$, further increasing s_E would never increase the generalized costs ϕ_E as this lane type has reached its maximum number of users. Increasing the capacity would only reduce ϕ_E, making the dedicated lanes more attractive, which implies that N_E remains equal to $\hat{N}_E$. For the case where $N_E < \hat{N}_E$ we observe through Equation (9) that this implies $\phi_E = \phi_R$ and $N_e = \frac{s_E}{s}N + \frac{s-s_E}{s}\sqrt{\frac{2M(\beta+\gamma)s_E}{\beta\gamma}}$. The derivative of N_E is defined for all non-negative road capacities s_E and is

$$\frac{\partial N_E}{\partial s_E} = \frac{N}{s} + \frac{s-3s_E}{2s\sqrt{s_E}}\sqrt{\frac{2M(\beta+\gamma)}{\beta\gamma}}. \tag{11}$$

Using that $N_E \geq \sqrt{\frac{2M(\beta+\gamma)s_E}{\beta\gamma}}$ (following indirectly from Equation (9)), $s_E \leq s$ and $N_e \leq N$, we can rewrite this to obtain $\frac{\partial N_E}{\partial s_E} \geq 0$. This concludes the first part of the lemma.

For the second part of the lemma, we assume by contradiction that $N_E < \hat{N}_E$ under the optimal road capacity s_E. As stated earlier in this proof, this implies $\phi_E = \phi_R$ and $N_e = \frac{s_E}{s}N + \frac{s-s_E}{s}\sqrt{\frac{2M(\beta+\gamma)s_E}{\beta\gamma}}$. We derive the derivatives of the generalized costs, which are identical given that $\phi_E = \phi_R$,

$$\frac{\partial \phi_R}{\partial s_E} = -\frac{\beta\gamma}{2s(\beta+\gamma)}\frac{x}{\sqrt{s_E}} < 0, \tag{12}$$

$$\frac{\partial \phi_E}{\partial s_E} = -\frac{\beta\gamma}{2s(\beta+\gamma)}\frac{x}{\sqrt{s_E}} < 0, \tag{13}$$

where $x = \sqrt{\frac{2M(\beta+\gamma)}{\beta\gamma}}$. As both derivatives are strictly negative, both ϕ_R and ϕ_E are decreasing in s_E. Thereby, N_E is increasing in s_E as per the first part of this lemma. It follows that the cost can be improved by increasing s_E, which increases N_E, showing that this situation is sub-optimal, contradicting with the earlier assumption. We have shown by contradiction that $N_E = \hat{N}_E$ under the optimal road capacity s_E. It follows directly that $N_R = \hat{N}_R$, concluding the second part of this proof. ■

Using Lemma 1 and the total cost definition in Equation (10), it can be shown that the optimal road capacity is a unique solution to a non-linear equality. In addition to this, the optimal road capacity is smaller than the maximum capacity for $M = 0$, as shown in Theorem 1.

Theorem 2. *For a budget $0 < M < \infty$, $\hat{N}_E > 0$ and $\hat{N}_R > 0$ it holds that the optimal road capacity s_E^* is the unique solution to the equality: $\frac{\hat{N}_R^2}{(s-s_E)^2} - \frac{\hat{N}_E^2}{s_E^2} + \frac{\hat{N}_E x}{2s_E^{1.5}} = 0$ with $x = \sqrt{\frac{2M(\beta+\gamma)}{\beta\gamma}}$. Thereby, $s_E^* \leq s\frac{\hat{N}_E}{\hat{N}_E+\hat{N}_R}$.*

Proof. We first consider the two border cases. Given that $\hat{N}_R > 0$, the optimal road capacity s_E^* is strictly smaller than s, because non-electric vehicles are not allowed on the dedicated lanes. Given that $\hat{N}_E > 0$ and $M > 0$, the optimal road capacity s_E^* is strictly larger than 0, because electric vehicles can benefit from incentives on the dedicated lanes, which reduces their generalized costs. Therefore, the optimal road capacity s_E^* is in the open interval $(0, s)$.[1]

Following from Lemma 1, it follows that $N_E = \hat{N}_E$ and $N_R = \hat{N}_R$ for the optimal road capacity s_E^*. We substitute these values, as well as the generalized costs, in Equation (10). We note that $s_R = s - s_E$ and take the derivative of the total cost to s_E, which should be equal to 0 at optimality. After some rewriting we obtain that $\frac{\partial TC}{\partial s_E} = f(s_E) = \frac{\hat{N}_R^2}{(s-s_E)^2} - \frac{\hat{N}_E^2}{s_E^2} + \frac{\hat{N}_E x}{2s_E^{1.5}} = 0$.

[1]We note that for the trivial cases where $\hat{N}_R = 0$, $\hat{N}_R = 0$ or $M = 0$, the border solutions may be a (non-unique) optimal solution.

We take the derivative of the left-hand side of this equation, which is defined for s_E strictly between 0 and s. By various substitutions, we obtain the following inequality. Here, first inequality follows from $N_E \geq \sqrt{s_E}x$, as per Equation (9) and the strict inequality follows from N_E and N_R being strictly positive.

$$\frac{\partial f(s_E)}{\partial s_E} = \frac{2N_R^2}{(s-s_E)^3} + \frac{2N_E^2}{s_E^3} - \frac{3N_E x}{4s_E^{2.5}} \tag{14}$$

$$\geq \frac{2N_R^2}{(s-s_E)^3} + \frac{2N_E^2}{s_E^3} - \frac{3N_E^2}{4s_E^3} \tag{15}$$

$$= \frac{2N_R^2}{(s-s_E)^3} + \frac{5N_E^2}{4s_E^3} \tag{16}$$

$$> 0. \tag{17}$$

It follows that $f(s_E)$ is strictly increasing. In addition to this, $\lim_{s_E \to 0^+} f(s_E) = -\infty$ and $\lim_{s_E \to s^-} f(s_E) = \infty$. Following from this, the solution to $f(s_E) = 0$ is unique and exists on the interval $(0, s)$.

Finally, substituting $\tilde{s}_E = s\frac{\hat{N}_E}{\hat{N}_E + \hat{N}_R}$ into $f(s_E)$ shows that $f(\tilde{s}_E) > 0$. Given that $\frac{\partial f(s_E)}{\partial s_E} > 0$ it holds that $s_E^* \leq \tilde{s}_E$, which concludes the proof. ■

3. RESULTS AND DISCUSSION

In this section we evaluate the combined use of incentives on electric vehicle charging and dedicated lanes for electric vehicles. We compare various scenarios to obtain policy implications and to evaluate the effectiveness of such a combined policy. We use the same parameter values as Arnott et al. (1990) and Cenedese et al. (2021), that were obtained based on the analysis of Small (1982). The unit cost parameters are $\alpha = 6.4[\$/\text{h}]$, $\beta = 3.9[\$/\text{h}]$ and $\gamma = 15.21[\$/\text{h}]$, the number of commuters $N = 9000$, and the bottleneck capacity $s = 60[\text{veh.}/\text{min}]$; thus the period considered lasts $T = 150$ min. We assume that the PEVs must charge for $\bar{\delta} = 20$ min. As a benchmark we use a single-lane scenario where all PEVs can access the charging station. We model this using the penetration rate theorey described by Sun et al. (2020), where the penetration rate is $p = \frac{\hat{N}_E}{\hat{N}_E + \hat{N}_R}$. They describe that the budget M is effective up to a maximum M^{p^*} and all the budget $M > M^{p^*}$ is wasted. The total cost associated to this benchmark with a budget M are displayed with a purple dashed line in every scenario.

The results are depicted in Figures 2 - 5. The first panel displays the total cost aggregated over the complete population. The black line in all panels indicates the value of s_E^*, i.e. the minimizer of the total costs. The second panel displays the generalized costs for PEVs and regular vehicles and the third panel displays the number of vehicles on each road type. Clearly, these empirical results confirm the theoretical results discussed in the previous section. Without incentives, the total costs increase when s_E exceeds $s\frac{\hat{N}_E}{\hat{N}_E + \hat{N}_R}$, which is caused by a bigger increase in ϕ_R compared to the decrease in ϕ_E. We also observe the non-uniqueness of the optimal capacity for $M = 0$, compared to the unique optimal solution for $M > 0$ which is lower than $s\frac{\hat{N}_E}{\hat{N}_E + \hat{N}_R}$. In addition to this, we observe that s_E^* decreases with the budget. This follows the intuition that the incentives can (partially) resolve the congestion for electric vehicles, such that more road capacity can be attributed to non-electric vehicles on which the incentives do not have a direct impact. This implies that when the lanes are segmented optimally, both electric vehicles and non-electric vehicles benefit from incentives on electricity charging.

In Figures 4 and 5 it is clear that increasing the road capacity dedicated to electric vehicle lanes beyond a certain threshold does not decrease the generalized costs for electric vehicles as congestion has been completely eliminated.

Comparing the lane segmentation policy to the situation where no lane segmentation exists, we observe that the performance strongly depends on the relation between M and M^{p^*}. In Figure 3, 4 and 5, the value of M^{p^*} is approximately \$3,900. Clearly, for a budget below this value, lane segmentation reduces the flexibility decreases the effect of incentives and therefore performs worse than a single-lane policy. When M exceeds M^{p^*} the additional budget is lost without lane segmentation and therefore the relative performance of the lane-segmentation policy starts to improve and even exceeds the no-segmentation policy for a budget of \$15,000. For the scenario depicted in Figure 5, lane segmentation can reduce the total costs by more than \$4,700, compared to when no lane segmentation is applied.

Overall, we observe that PEV owners are better off than owners of non-electric vehicles, as at the optimal road capacity and in equilibrium their generalized costs are lower ($\phi_E < \phi_R$). Clearly, this has an advantageous secondary effect which is that people are stimulated to switch to electric vehicles, which can reduce the number of fossil-fueled vehicle in the long term.

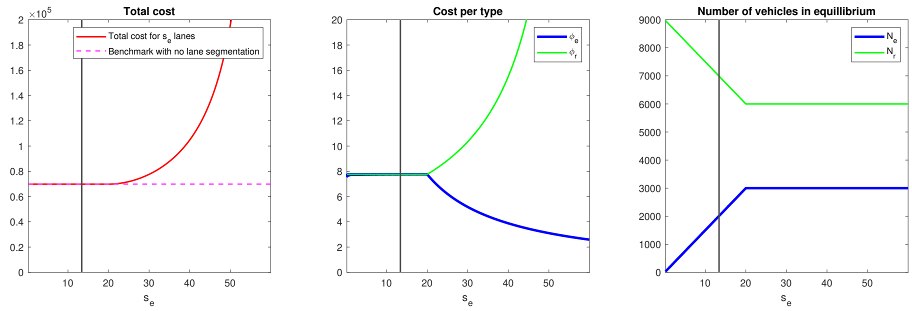

Figure 2: No incentives ($M = \$0$)**,** $\hat{N}_R = 6000$**,** $\hat{N}_E = 3000$

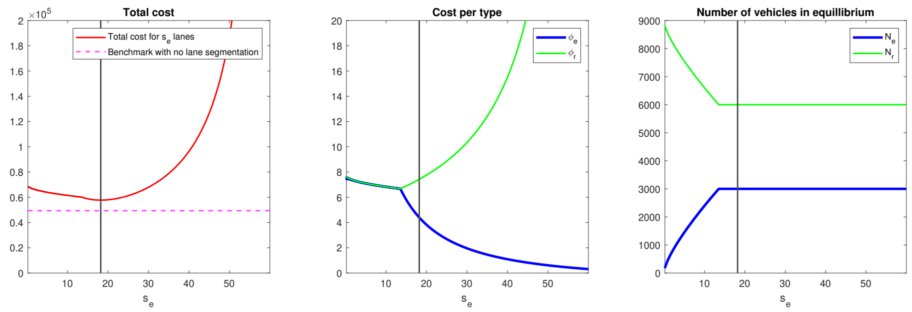

Figure 3: $M = \$3,000$**,** $\hat{N}_R = 6000$**,** $\hat{N}_E = 3000$

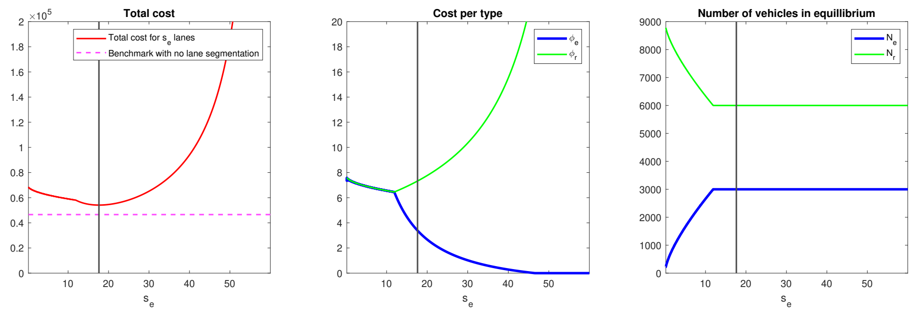

Figure 4: $M = \$5,000$**,** $\hat{N}_R = 6000$**,** $\hat{N}_E = 3000$

4. CONCLUSIONS

In this work, we have shown some important properties of dedicated lanes for electric vehicles in the presence of incentives on electric vehicle charging. The optimal road capacity is decreasing in

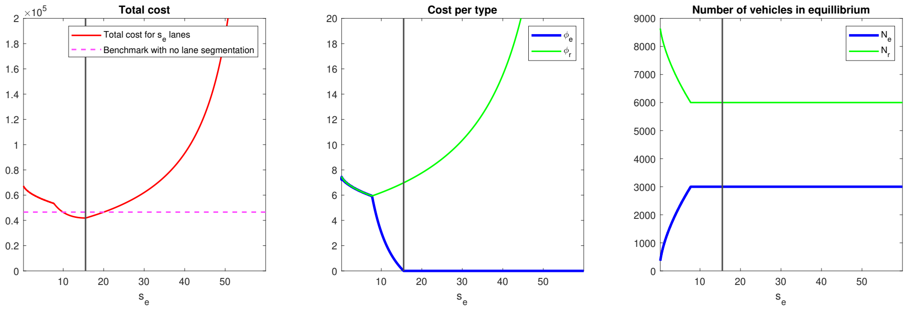

Figure 5: $M = \$15,000$, $\hat{N}_R = 6000$, $\hat{N}_E = 3000$

the incentive budget but increasing in the number of PEV owners. Thereby, we have shown that for a positive incentive budget and under the optimal road capacity, all PEVs are driving on the dedicated electric vehicle lanes. Finally, we have shown that for reasonable non-trivial scenarios, there exists a unique optimal solution to the lane segmentation problem.

We conclude that lane-segmentation is superior to a policy without lane segmentation for large budgets. The reason for this is that without lane segmentation, additional budget becomes useless beyond a certain threshold. With lane segmentation, this threshold can be exceeded to further reduce the total cost experienced by all travelers. Thereby, incentives on electric vehicle charging combined with lane segmentation can stimulate the use of electric vehicles in the long run. The reason for this is that lane segmentation allows the generalized costs for PEVs to go below the generalized costs of regular vehicles in equilibrium, such that PEV owners are generally better off. When no lane segmentation is applied, their costs are equal in equilibrium and therefore the use of electric vehicles over non-electric vehicles is not stimulated.

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