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Congestion and emissions mitigation: A comparison of capacity, demand, and vehicle based strategies

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ABSTRACT

Capacity, demand, and vehicle based emissions reduction strategies are compared for several pollutants employing aggregate US congestion and vehicle fleet condition data. We find that congestion mitigation does not inevitably lead to reduced emissions; the net effect of mitigation depends on the balance of induced travel demand and increased vehicle efficiency that in turn depend on the pollutant, congestion level, and fleet composition. In the long run, capacity-based congestion improvements within certain speed intervals can reasonably be expected to increase emissions of CO_2e, CO, and NO_x through increased vehicle travel volume. Better opportunities for emissions reductions exist for HC and $PM_{2.5}$ emissions, and on more heavily congested arterials. Advanced-efficiency vehicles with emissions rates that are less sensitive to congestion than conventional vehicles generate less emissions co-benefits from congestion mitigation.

1. Introduction

In many cases, emissions reductions are cited as an implicit benefit of congestion mitigation without proper justification or quantification of the benefits. For example, the US Federal Highway Administration's Congestion Mitigation and Air Quality (CMAQ) improvement program suggests a clear co-beneficial relationship. If congestion mitigation is to be tied to air quality goals, we need better understanding of congestion impacts on motor vehicle emissions.

Vehicle emissions from motorized transportation have an established role in decreasing urban air quality and increasing atmospheric greenhouse gases. Concurrently, roadway congestion impacts urban areas throughout the world with varying economic, social, and environmental costs. But the full effects of traffic congestion on motor vehicle emissions are still not well quantified due to the existence of feedback effects and complex interactions. Potential changes in travel behavior or vehicle technology are two factors that complicate the evaluation of congestion mitigation effects on future emissions.

An important consideration to evaluate the impact of congestion mitigation measures on emissions is the effect of induced travel demand volume resulting from travel time savings. A report by Dowling (2005) used travel demand modeling to estimate the air quality effects of traffic flow improvements. The conclusion of the report states that more research is needed "to better understand the conditions under which traffic-flow improvements contribute to an overall net increase or decrease in vehicle emissions." Other, more focused research on a limited spatial scale has shown that induced demand from individual traffic flow improvements can entirely offset emissions rate reductions (Stathopoulos and Noland, 2003; Noland and Quddus, 2006).

Capacity-based strategies (CBSs) for reducing emissions ease congestion by increasing a roadway's vehicle throughput capacity and so increase vehicle operating efficiency. CBS can increase capacity by increasing physical lane-miles or by

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increasing existing roadway utilization through traffic flow improvements. The desired emissions benefit of congestion mitigation through CBS is reduced marginal emissions rates at higher average traffic speeds. However, it has the potential to generate induced vehicle travel demand.

Alternative strategies for reducing emissions can be vehicle based strategies (VBS) or demand based strategies (DBS). VBS directly target emissions through cleaner vehicles and fuels or more efficient driving. DBS, such as road pricing, reduce emissions by reducing vehicle travel volume and can reduce congestion simultaneously.

Here we investigate the broad conditions in which emissions co-benefits can be expected from congestion mitigation and compare capacity, demand, and vehicle based emissions reduction strategies. In particular, we study the effects of travel demand elasticity, the consequences of advanced vehicles in the fleet, and the role of light-duty and heavy-duty vehicles across types of pollutants. The methodological framework allows for a parsimonious estimation of net emissions effects at the aggregated level.

2. Methodological framework

The concept of elasticity is employed to set up the conditions that lead to positive or negative net emissions changes. The elasticity, $\varepsilon_{\bar{e}}^{\bar{v}}$, of average emissions rate, $\bar{e}$, to average travel speed, $\bar{v}$, is expressed

$$\varepsilon_{\bar{e}}^{\bar{v}} = \frac{\bar{v}}{\bar{e}} \cdot \frac{\partial \bar{e}}{\partial \bar{v}}. \tag{1}$$

The average vehicle emissions rate in mass per unit distance of travel is denoted as $\bar{e}$, and emissions from all on-road vehicles in mass per unit length of road, per unit of time is denoted as E. If the vehicle travel demand volume on a roadway is q (in vehicle throughput per unit time), then $E = q \cdot \bar{e}$. The average travel speed on the roadway is denoted as $\bar{v}$, in distance traveled per unit time.

The *long-term* elasticity of travel demand volume q to average speed $\bar{v}$ is expressed

$$\eta_q^{\bar{v}} = \frac{\bar{v}}{q} \cdot \frac{\partial q}{\partial \bar{v}}. \tag{2}$$

The value of $\eta_q^{\bar{v}}$ represents the percentage change in vehicle miles traveled (VMT) with a one percent $\bar{v}$ change on a roadway of arbitrary length. The elasticity of E to $\bar{v}$ is then

$$\varepsilon_E^{\bar{v}} = \frac{\bar{v}}{E} \cdot \frac{\partial E}{\partial \bar{v}} = \frac{\bar{v}}{q \cdot \bar{e}} \left(\frac{\partial q}{\partial \bar{v}} \cdot \bar{e} + q \cdot \frac{\partial \bar{e}}{\partial \bar{v}} \right) = \eta_q^{\bar{v}} + \varepsilon_{\bar{e}}^{\bar{v}}. \tag{3}$$

This relationship, $\varepsilon_E^{\bar{v}} = \eta_q^{\bar{v}} + \varepsilon_{\bar{e}}^{\bar{v}}$, is the central equation of the methodological framework; it expresses the elasticity of emissions to average travel speed as the combined effects of changes in travel demand volumes and emission rates. The break-even travel demand elasticity to speed, denoted $\gamma_q^{\bar{v}}$, that produces the condition $\varepsilon_E^{\bar{v}} = 0$ is $\gamma_q^{\bar{v}} = -\varepsilon_{\bar{e}}^{\bar{v}}$. It follows that:

$$\varepsilon_E^{\bar{v}} = \eta_q^{\bar{v}} - \gamma_q^{\bar{v}} \tag{4}$$

the difference between true demand elasticity and break-even demand elasticity is the emissions elasticity to speed.

The preceding equations are for an aggregate vehicle fleet; to understand the impacts of vehicle classes, additional notation and formulae are needed. For vehicles of class j (in the mutually exclusive and exhaustive set of vehicle classes J), the average emissions rate is e_j and travel demand volume is q_j. The fraction of on-road vehicles that are of class j (by distance traveled) is f_j, so that $f_j = \frac{q_j}{q}$. Class-total emissions are $E_j = q_j \cdot e_j = q \cdot f_j \cdot e_j$, and the elasticities $\varepsilon_{E_j}^{v_j}$, $\eta_{q_j}^{v_j}$, and $\varepsilon_{e_j}^{v_j}$ are similar to the ones defined previously, but only for vehicles of class j. Total emissions, E, from on-road vehicles of all classes in J, per unit length of road per unit time, are the sum of each class's emissions $E = \sum_{j \in J} E_j = \sum_{j \in J} (q_j \cdot e_j)$. From this,

$$E = q \cdot \sum_{j \in J} (f_j \cdot e_j) = q \cdot \bar{e}. \tag{5}$$

Employing $\varepsilon_{E_j}^{v_j} = \frac{v_j}{E_j} \cdot \frac{\partial E_j}{\partial v_j}$, the elasticity of E to $\bar{v}$ considering distinct vehicle classes is

$$\begin{aligned} \varepsilon_E^{\bar{v}} &= \frac{\bar{v}}{E} \cdot \frac{\partial \sum_{j \in J} E_j}{\partial \bar{v}} = \frac{\bar{v}}{E} \cdot \sum_{j \in J} \left[\frac{\partial E_j}{\partial v_j} \cdot \frac{\partial v_j}{\partial \bar{v}} \right], \\ \varepsilon_E^{\bar{v}} &= \frac{\bar{v}}{q \cdot \bar{e}} \cdot \sum_{j \in J} \left[\frac{E_j}{v_j} \cdot \varepsilon_{E_j}^{v_j} \cdot \frac{\partial v_j}{\partial \bar{v}} \right], \\ \varepsilon_E^{\bar{v}} &= \frac{\bar{v}}{\bar{e}} \cdot \sum_{j \in J} \left[\frac{f_j e_j}{v_j} \cdot \varepsilon_{E_j}^{v_j} \cdot \frac{\partial v_j}{\partial \bar{v}} \right]. \end{aligned} \tag{6}$$

If we assume that speed changes proportionally for all vehicle classes, $\frac{\partial v_j}{\partial \bar{v}} = \frac{v_j}{\bar{v}} \forall j \in J$, then

$$\varepsilon_E^{\bar{v}} = \frac{1}{\bar{e}} \cdot \sum_{j \in J} \left[e_j \cdot f_j \cdot \varepsilon_{E_j}^{v_j} \right] = \sum_{j \in J} \left[\frac{E_j}{E} \cdot \varepsilon_{E_j}^{v_j} \right]. \tag{7}$$

Table 1
MOVES emissions-speed curve fit parameters for $\bar{e}$ and e_j.

	CO_2e	CO	$PM_{2.5}$	NO_x	HC
Full fleet					
a_0	8.191	2.885	−1.223	1.897	0.3352
a_1	−0.1826	−0.1788	−0.1769	−0.1656	−0.2040
a_2	0.006339	0.006629	0.006640	0.005830	0.006643
a_3	−9.690E−05	−1.092E−04	−1.127E−04	−8.928E−05	−1.012E−04
a_4	5.357E−07	6.518E−07	6.724E−07	4.936E−07	5.674E−07
LD vehicles					
$a_{0,l}$	7.987	2.788	−2.856	0.3239	−0.2644
$a_{1,l}$	−0.1856	−0.1760	−0.2000	−0.1152	−0.1878
$a_{2,l}$	0.006352	0.006535	0.007365	0.004155	0.006173
$a_{3,l}$	−9.550E−05	−1.077E−04	−1.157E−04	−6.270E−05	−9.570E−05
$a_{4,l}$	5.210E−07	6.460E−07	6.560E−07	3.440E−07	5.510E−07
HD vehicles					
$a_{0,h}$	9.254	3.541	1.005	4.124	2.059
$a_{1,h}$	−0.1748	−0.1900	−0.1740	−0.1839	−0.2206
$a_{2,h}$	0.006307	0.006843	0.006599	0.006461	0.006967
$a_{3,h}$	−1.007E−04	−1.097E−04	−1.141E−04	−1.003E−04	−1.018E−04
$a_{4,h}$	5.740E−07	6.201E−07	6.870E−07	5.599E−07	5.380E−07

From this equation, emissions break-even conditions can also exist when decreased emissions from one vehicle class offset increased emissions from another, in addition to the general (trivial) case where $\varepsilon_{E_j}^{v_j} = 0 \forall j \in J$.

Following previous emissions research (Sugawara and Niemeier, 2002; Barth and Boriboonsomsin, 2008), the functional form for $\bar{e} = f(\bar{v})$ employed in this paper is

$$\bar{e}(\bar{v}) = \exp\left(\sum_{i=0}^{n}[a_i \cdot \bar{v}^i]\right), \tag{8}$$

where a_i are fitted parameters and $n = 4$. Similarly, class-average emissions rates, e_j, as a function of v_j are

$$e_j(v_j) = \exp\left(\sum_{i=0}^{n}[a_{i,j} \cdot v_j^i]\right). \tag{9}$$

The curves defined by Eqs. (8) and (9) are henceforth referred to as emissions-speed curves (ESC). By differentiating these ESC,

$$\varepsilon_{\bar{e}}^{\bar{v}} = \sum_{i=1}^{4}(ia_i\bar{v}^i) \quad \text{and} \quad \varepsilon_{e_j}^{v_j} = \sum_{i=1}^{4}\left(ia_{i,j}v_j^i\right). \tag{10}$$

Note that $\varepsilon_{\bar{e}}^{\bar{v}}$, and $\gamma_q^{\bar{v}}$, are independent of q as long as $\bar{e} = f(\bar{v})$; the same independence from q holds for the class-specific variables.

ESC parameters a_i and $a_{i,j}$ are estimated using data points generated from the Motor Vehicle Emissions Simulator (MOVES) 2010 model from the US Environmental Protection Agency (EPA) (2009a). The pollutants modeled are CO_2e (greenhouse gases in carbon dioxide equivalent units), CO (carbon monoxide), NO_x (nitrogen oxides), $PM_{2.5}$ (particulate matter smaller than 2.5 μm), and HC (hydrocarbons). Emissions rates are modeled at 16 discrete average speeds (in 5 mph increments), and the parameters a_i and $a_{i,j}$ are estimated by minimizing squared error, with $\bar{e}$ and e_j in grams per vehicle-mile and $\bar{v}$ and v_j in miles per hour (mph). Note that $\bar{v}$ and v_j do not represent constant-speed driving, but are instead facility-specific average speeds representing archetypal driving speed profiles.

The fitted ESC obtain $R^2 > 0.96$ for all five pollutants. Fitted parameters a_i and $a_{i,j}$ are shown in Table 1 for the full vehicle fleet and for light-duty (LD) and heavy-duty (HD) portions of the vehicle fleet on freeways for April 2010. The modeled full fleet is composed of 8.9% HD vehicles. Separate parameters are estimated for arterial emissions rates.

3. Emissions impacts of CBS

The long-term net emissions effects of CBS can be estimated as $\varepsilon_E^{\bar{v}}$ from Eq. (3), with modeled values for a_i and an expected value for travel demand elasticity, $\eta_q^{\bar{v}}$ (which is highly uncertain). To estimate only the sign of net changes in emissions it is only necessary to determine the value of the break-even demand elasticity $\gamma_q^{\bar{v}}$, which is dependent on average travel speed, vehicle fleet composition, and ESC parameters. Three distinct scenarios are possible: (a) if $\eta_q^{\bar{v}} < \gamma_q^{\bar{v}}$ then CBS will likely decrease emissions, (b) if $\eta_q^{\bar{v}} > \gamma_q^{\bar{v}}$ then CBS will likely *increase* emissions, and (c) if $\eta_q^{\bar{v}} = \gamma_q^{\bar{v}}$ then emissions are likely to be unaffected by changes in capacity and congestion in the long term.

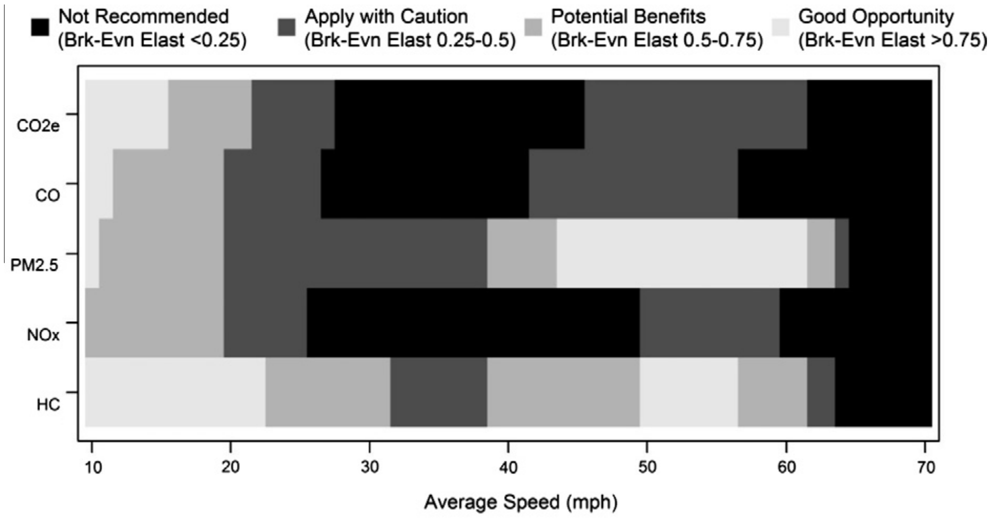

Fig. 1. Characterization of CBS for emissions reductions.

Previous works suggest that likely values of induced demand from capacity increases are in the range: $0.2 < \eta_q^{\bar{v}} < 1.0$. Using this range of likely elasticity values, Fig. 1 shows qualitative characterizations of expected emissions effects of CBS for each pollutant over a range of speeds for the full-modeled fleet on freeways – based on $\gamma_q^{\bar{v}} = -\sum_{i=1}^{4}(ia_i\bar{v}^i)$ and a_i from Table 1. As an emissions-reducing strategy, CBS are "not recommended" for $\gamma_q^{\bar{v}} < 0.25$; CBS are suggested to "apply with caution" for $0.25 \leqslant \gamma_q^{\bar{v}} < 0.5$; CBS have "potential benefits" for $0.5 \leqslant \gamma_q^{\bar{v}} < 0.75$; and CBS provide "good opportunity" for emissions reductions for $0.75 \leqslant \gamma_q^{\bar{v}}$.

Beyond the potential subjectivity of the classification, it is evident from Fig. 1 that CBS will have significantly different net impacts across pollutants. $PM_{2.5}$ and HC have the widest range of speeds for which CBS are likely to reduce emissions. The other pollutants (CO_2e, CO, and NO_x) are only classified as "potential benefits" or better at speeds of about 20 mph and below – suggesting emissions increases from CBS above 20 mph. CBS are "not recommended" for all pollutants at speeds above 65 mph, showing the emissions benefits from limiting free-flow speeds to below 65 mph.

The characterizations in Fig. 1 assume similar responses by vehicle type. Now consider a binary segmentation of the vehicle fleet where $j = l$ is all LD vehicles and $j = h$ is all HD vehicles: $\{j = l, h\}$. If we assume the extreme case of $\eta_{qh}^{vh} = 0$ (inelastic HD vehicle travel demand to travel speed), then from Eq. (7), $\varepsilon_E^{\bar{v}} = 0$ when $\eta_{ql}^{v_l} = -\left(\frac{e_h \cdot f_h}{e_l \cdot f_l} \cdot \varepsilon_{e_h}^{v_h} + \varepsilon_{e_l}^{v_l}\right)$. Based on this net break-even demand elasticity for LD vehicles, Fig. 2 shows a similar characterization of CBS to Fig. 1, but assuming $\eta_{qh}^{vh} = 0$ (with initial $f_h = 0.09$ and $a_{i,j}$ from Table 1).

The demand elasticity of HD vehicles is a major factor to determine net emissions changes. In Fig. 2 there is a wider array of speeds for all pollutants that present opportunities for emissions reductions through CBS than in Fig. 1. For $PM_{2.5}$ and HC good opportunities exist for emissions reductions from CBS all the way up above 60 mph. Although this is perhaps an

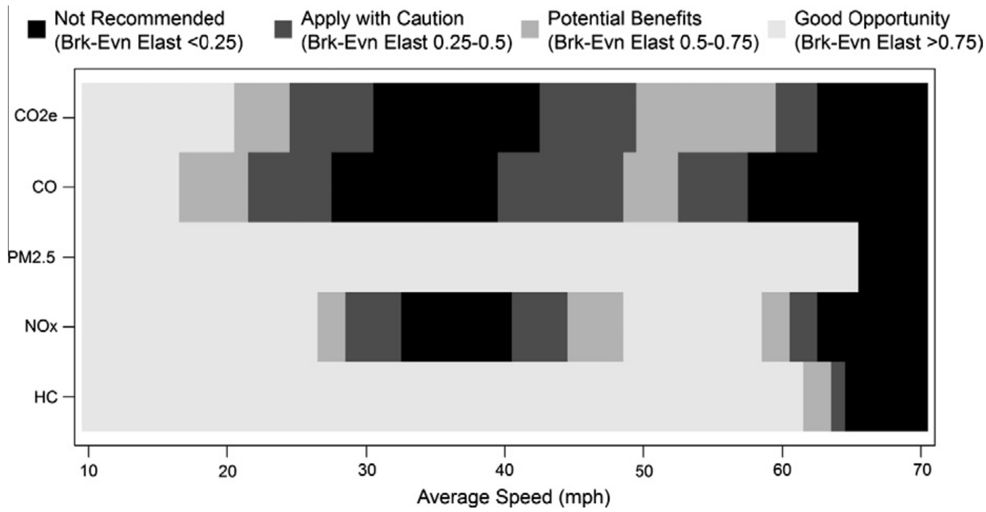

Fig. 2. Characterization of CBS based on break-even demand elasticity for LD vehicles, assuming inelastic HD demand.

extreme value of demand elasticity for HD vehicles, it demonstrates that even at only 9% of the fleet, η_{qh}^{vh} is an important consideration for predicting emissions effects of congestion mitigation.

For this analysis to apply, CBS are not necessarily additional lane-miles. Capacity or throughput can also be increased by various traffic management strategies that target roadway efficiency and utilization such as lane change restrictions on freeways or effective management of variable speed limits. The key to the effects demonstrated here is an increase in average travel speed with baseline or higher traffic volumes.

Some traffic management techniques could have implications for vehicle speed profiles that would affect estimates of $a_{i,j}$ (we assumed $a_{i,j}$ parameters do not change in Figs. 1 and 2). For example, a significant "smoothing" of vehicle speeds could reduce the average emissions rate at a given average travel speed by reducing engine loads (Barth and Boriboonsomsin, 2008). This change in the ESC parameters would have to be considered in concert with any changes in average travel speed or travel demand volume, but the same methodology can be applied to estimate long-term emissions impacts of CBS.

Similarly, emissions rates are expected to trend downward over time. If the *shape* of the ESC (i.e. $\varepsilon_{\bar{e}}^{\bar{v}}$) do not change, then the analysis is unaffected. If, on the other hand, advances in vehicle technology lead to vehicles that are less sensitive to congestion (i.e. flatter ESC), then the prospects of CBS are affected.

4. The impacts of more efficient vehicles (VBS)

The results in Section 3 are for conventional internal combustion engine (ICE) vehicles only – the vast majority of the existing on-road fleet (US Environmental Protection Agency, 2009b). We now examine the effects of introducing advanced vehicles in the fleet, a form of VBS. By reducing $\bar{e}$, VBS decrease emissions as $\frac{\partial E}{\partial \bar{e}} = q$ (from Eq. (5)), and thus $\varepsilon_E^{\bar{e}} = 1$. But VBS can also impact the efficacy of CBS for emissions reductions. Let vehicle class $j = c$ be all conventional ICE vehicles, vehicle class $j = e$ be Electric Vehicles (EV), and vehicle class $j = a$ be other Advanced Efficiency (AE) vehicles. This is the complete set of vehicles, $J = \{c, a, e\}$, with emissions of $E = E_c + E_a + E_e$. The emissions elasticity to speed, from Eq. (7), is then

$$\varepsilon_E^{\bar{v}} = \frac{E_c}{E}\varepsilon_{E_c}^{v_c} + \frac{E_a}{E}\varepsilon_{E_a}^{v_a} + \frac{E_e}{E}\varepsilon_{E_e}^{v_e}. \tag{11}$$

The AE vehicle class contains vehicles (such as many gas-electric hybrids) with regenerative braking and other improvements that render them less sensitive or insensitive to low-speed inefficiencies: i.e. $|\varepsilon_{e_a}^{v_a}| < |\varepsilon_{e_c}^{v_c}|$. Then, because $\varepsilon_{v_c}^{e_c}$ is expected to be negative through most of the range of feasible speeds according to the MOVES-based ESC, $\varepsilon_{e_c}^{v_c} < \varepsilon_{e_a}^{v_a} \leqslant 0$. Considering only emissions from ICE and AE vehicles ($E = E_c + E_a$), Eq. (11) reduces to

$$\varepsilon_E^{\bar{v}} = \frac{E_c}{E}\varepsilon_{E_c}^{v_c} + \frac{E_a}{E}\varepsilon_{E_a}^{v_a} = \varepsilon_{E_c}^{v_c} - \frac{E_a}{E}\left(\varepsilon_{E_c}^{v_c} - \varepsilon_{E_a}^{v_c}\right). \tag{12}$$

If we assume that travel demand elasticity is unaffected by vehicle type, $\eta_{q_j}^{v_j} = \eta_q^{\bar{v}} \forall j$, then using $\varepsilon_{E_j}^{v_j} = \eta_{q_j}^{v_j} + \varepsilon_{e_j}^{v_j}$, Eq. (12) further reduces to

$$\varepsilon_E^{\bar{v}} = \varepsilon_{E_c}^{v_c} - \frac{E_a}{E}\left(\varepsilon_{e_c}^{v_c} - \varepsilon_{e_a}^{v_a}\right). \tag{13}$$

The value of $\varepsilon_{e_c}^{v_c} - \varepsilon_{e_a}^{v_a}$ is expected to be negative because it is assumed that $\varepsilon_{e_c}^{v_c} < \varepsilon_{e_a}^{v_a} \leqslant 0$. Thus, with an increase in E_a (because of higher f_a or e_a), $\varepsilon_E^{\bar{v}}$ increases, too (becomes more positive or less negative). In other words, emissions are more likely to increase with speed when there are more or higher-emitting AE vehicles in the fleet. The change can be explained by lower emissions rate sensitivity to speed for AE vehicles: AE vehicles have less efficiency improvement than ICE vehicles with increasing speed, but still are subject to increased emissions through induced demand.

From Eq. (13), emissions break-even conditions ($\varepsilon_E^{\bar{v}} = 0$) exist when $\varepsilon_{E_c}^{v_c} = \frac{E_a}{E}\left(\varepsilon_{e_c}^{v_c} - \varepsilon_{e_a}^{v_a}\right)$, or substituting and combining terms,

$$\eta_q^{\bar{v}} = \frac{E_c}{E}\gamma_{q_c}^{v_c} + \frac{E_a}{E}\gamma_{q_a}^{v_a}. \tag{14}$$

Because $\varepsilon_{e_c}^{v_c} < \varepsilon_{e_a}^{v_a} \leqslant 0$, we expect that $\gamma_{q_c}^{v_c} > \gamma_{q_a}^{v_a} \geqslant 0$, and thus the break-even demand elasticity with AE vehicles present is smaller than for ICE vehicles alone ($\gamma_{q_c}^{v_c}$). In the extreme case, AE vehicles have emissions rates that are non-zero ($e_a \neq 0$) but that are insensitive to congestion level and average speed, $\varepsilon_{e_a}^{v_a} = \gamma_{q_a}^{v_a} = 0$. Then Eq. (14) reduces to $\eta_q^{\bar{v}} = \frac{E_c}{E}\gamma_{q_c}^{v_c}$ and the break-even demand elasticity is smaller in proportion to the fractional ICE emissions out of emissions. Smaller values of break-even demand elasticity suggest *less* potential for emissions benefits from congestion mitigation. More AE vehicles are expected to decrease emissions as they replace ICE vehicles, as long as $e_a < e_c$; but efficiency gains through speed increases are more likely to be cancelled out by induced demand, and CBS are less likely to be an effective emissions reduction strategy with more AE vehicle emissions.

Regarding electric vehicles, if EV emissions are zero ($e_e = 0$ and by extension $\frac{\partial e_e}{\partial v_e} = \varepsilon_{e_c}^{v_c} = 0$), then Eqs (13) and (14) still apply. Unless a change in f_e affects the fraction of AE vehicle emissions $\frac{E_a}{E}$ through a change in $\frac{f_a}{f_c}$, the emissions elasticity to speed $\varepsilon_E^{\bar{v}}$ is independent of the fraction of EV in the fleet, f_e (even though EV's reduce emissions on a per-vehicle basis). Similarly, if the presence of EV's does not affect $\frac{f_a}{f_c}$, then the EV's will not impact break-even demand elasticity. If we choose to consider the upstream emissions for EV that are generated during the electric power production process (i.e. using a "well-to-wheels"

Table 2
Equivalent emissions reduction strategies for freeway CO_2e $\left(\eta_q^{\bar{v}} = 0.3\right)$.

	19–31 mph	31–53 mph	53–60 mph
Avg. speed change (mph)	11.9 (64%)	22.4 (73%)	6.8 (13%)
Travel demand change (vehicle miles/peak traveler-day)	0.7 (9%)	0.8 (10%)	0.2 (2%)
Net emissions change (g CO_2e/peak traveler-day)	−131 (−3%)	112 (3%)	−31 (−1%)
Alternative demand strategy			
Trip length change (vehicle miles/peak traveler-day)	−0.2 (−3%)	0.2 (3%)	−0.1 (−1%)
Alternative vehicle efficiency strategies			
Vehicle fuel efficiency change (miles/gallon)	0.5 (3%)	−0.5 (−3%)	0.2 (1%)
Fuel carbon intensity change (kg CO_2e/gallon)	−0.3 (−3%)	0.3 (3%)	−0.1 (−1%)
EV penetration by LCA (% of peak period fleet)	8%	−9%	3%
EV penetration by zero-emissions (% of peak period fleet)	4%	−4%	1%

approach or life-cycle assessment (LCA)), then $0 < e_e < e_c$ and we can represent EV as a new type of AE vehicle – and the previous Eqs. (13) and (14) are still applicable.

5. Travel volume reductions and emissions

In terms of the methodological framework, by reducing q, DBS decrease emissions as $\frac{\partial E}{\partial q} = \bar{e}$ (from Eq. (5)), or $\varepsilon_E^q = 1$. But DBS also relate to congestion through the CBS analysis. When $\eta_q^{\bar{v}} > \gamma_q^{\bar{v}}$, average speed-based efficiency alone cannot reduce emissions because of induced travel demand. From the DBS perspective, when $\eta_q^{\bar{v}} > \gamma_q^{\bar{v}}$ a capacity decrease (i.e. "road diet") can reduce emissions if the suppressed travel demand volume offsets higher vehicle emission rates at lower average travel speeds. In other words, with a capacity-based approach, lower emissions are more likely by increasing capacity when $\eta_q^{\bar{v}} > \gamma_q^{\bar{v}}$ and by *decreasing* capacity when $\eta_q^{\bar{v}} > \gamma_q^{\bar{v}}$.[1]

In other forms of DBS vehicle travel demand volume is reduced by motivators such as road pricing or travel restrictions. For the demand volume change alone the emissions effect is indicated by $\varepsilon_E^q = 1$. If the DBS impacts congestion or is jointly implemented with a CBS, the key value for application of this analysis is the *net* travel demand elasticity to travel speed. For example, if a demand-moderating measure such as road pricing is implemented along with a capacity expansion, then that effect can be incorporated as a lower expected range of $\eta_q^{\bar{v}}$. In the best case (for emissions), both increased average travel speeds and reduced vehicle travel demand volume (i.e. $\eta_q^{\bar{v}} < 0$) contribute to a reduction of emissions; e.g. strong pricing programs such as implemented in London (Beevers and Carslaw, 2005).

6. Comparing strategies for emissions reductions

Initially we look at freeways, comparing VBS and DBS to CBS that increase congested speeds as indicated by a level-of-service (LOS) change.[2] The comparison is presented as the amount of a VBS or DBS that would achieve equivalent emissions reductions to the CBS. Results for CO_2e emissions are shown in Table 2 using $\eta_q^{\bar{v}} = 0.3$ (a relatively low demand elasticity value). The three numerical columns in Table 2 (from left to right) show LOS changes from F to E, from E to D, and from D to the A–C range. For each hypothetical LOS improvement the net changes in average speed, travel demand volume, and peak period emissions are shown in the first three rows of the Table. Only emissions from peak-period freeway travel are included, and the LOS changes only apply to the congested portion of freeway travel: 55%.

The final rows in Table 2 show the VBS and DBS changes that would be required to generate the same peak period emissions changes on freeway facilities from each alternative strategy. The VBS and DBS effects apply to all peak-period freeway travel; other impacts are excluded (e.g. EV ownership would also reduce emissions from non-peak period trips and from travel on non-freeway facilities).

As an example, consider the first numerical column of Table 2, which considers CO_2e emissions for a freeway LOS change from F to E. The average speed change on congested freeways from 19 to 31 mph (rounded) is a speed increase of 64%; row 1. Assuming $\eta_q^{\bar{v}} = 0.3$, this speed increase leads to 0.7 additional vehicle-miles of peak period freeway travel (per peak period traveler per day), an increase of 9%; row 2. Considering the increased efficiency and induced demand, CO_2e emissions are reduced fall by 3%; row 3. This 131 g of emissions savings could also have been achieved by reducing daily peak-period freeway travel by 3% vehicle-miles per peak period; row 4. Alternatively, 131 g of CO_2e could be saved if daily peak-period freeway travel were in vehicles with 3% higher average per gallon fuel economy; row 5. A decrease of 0.3 kg CO_2e per gallon in the carbon intensity of fuel burned during peak-period freeway travel could also save 131 g of CO_2e emissions; row 6. Finally,

[1] This assumes that demand elasticities to speed changes in each direction are the same – i.e. the aggregate travel response to a speed increase is equal and opposite of the response to a speed decrease.

[2] LOS is used as a qualitative congestion indicator, with average speeds for freeways from Barth et al. (1999). LOS F is the most congested, while LOS A through C are essentially at free-flow speeds.

Table 3
Equivalent emissions reduction strategies for arterial CO_2e $\left(\eta_q^{\bar{v}} = 0.3\right)$.

	10–16 mph	16–24 mph	24–35 mph
Avg. speed change (mph)	6.0 (60%)	8.0 (50%)	11.0 (46%)
Travel demand change (vehicle miles/peak traveler-day)	0.7 (9%)	0.6 (8%)	0.6 (7%)
Net Emissions change (g CO_2e/peak traveler-day)	−1002 (−15%)	−374 (−7%)	31 (1%)
Alternative demand strategy			
Trips length change (vehicle miles/peak traveler-day)	−1.3 (−15%)	−0.6 (−7%)	0.1 (1%)
Alternative vehicle efficiency strategies			
Vehicle fuel efficiency change (miles/gallon)	1.9 (17%)	1.1 (8%)	−0.1 (−1%)
Fuel carbon intensity change (kg CO_2e/gallon)	−1.3 (−15%)	−0.6 (−7%)	0.1 (1%)
EV penetration by LCA (% of peak period fleet)	29%	17%	−2%
EV penetration by zero-emissions (% of peak period fleet)	19%	9%	−1%

converting 8% (by LCA) or 4% (by zero-emissions estimation) of the LD vehicle fleet to EV's for peak-period freeway travel could also achieve the same savings of 131 g CO_2e; rows 7 and 8.

As expected from previous results, the LOS change from F to E generates the greatest emissions benefits in Table 2, which require the largest alternative strategies to match. These alternative strategies, subjectively modest but in some cases difficult to implement, have the potential for low or zero capital costs for transportation agencies (but lower fuel tax revenue). On the other hand, capital improvement projects for CBS such as urban freeway widening can be extremely expensive endeavors (but they can increase fuel consumption and associated tax revenues).

At the moderate demand elasticity of $\eta_q^{\bar{v}} = 0.3$ the induced travel for LOS E to LOS D leads to an emissions increase. When an emissions increase is expected, the alternative strategy equivalents have opposite signs from an emissions savings – i.e. longer trips, reduced vehicle efficiency, higher fuel carbon intensity, and fewer EV's in the fleet. Using an assumed elasticity of $\eta_q^{\bar{v}} = 0.5$ the induced travel leads to emission increases for all three LOS improvements in Table 2.

Table 3 shows the results of an equivalent analysis for CO_2e emissions on arterials, again with a demand elasticity of $\eta_q^{\bar{v}} = 0.3$. Table 3 uses travel speed increases of 10–16 mph, 16–24 mph, and 24–35 mph, roughly parallel to the heavily congested – moderately congested – uncongested LOS improvements in Table 2. As expected for a lower-speed facility, arterial congestion mitigation is more effective at reducing emissions rates. Still, even with this moderate demand elasticity the speed improvement above 24 mph produces a net emissions increase because of induced demand.

The values in row 4 of Tables 2 and 3 associated with VMT reductions (DBS) assume a fixed number of peak period travelers and no change in average emissions rates (i.e., shorter or longer trips but the same and $\bar{v}$ and $\bar{e}$). The values in rows 5–8 (VBS) assume no changes in $\bar{v}$. Values in row 7 of Tables 2 and 3 assume an EV carbon intensity of travel of 0.216 kg CO_2e - per mile (Samaras and Meisterling (2008)) based on LCA, although upstream emissions are not included in the on-road emissions estimates for ICE vehicles (a conservative approach). Tables 2 and 3, row 8, assume zero emissions for EV's; the assumption of zero emissions for EV's is also made for local pollutants.

Additional assumptions underlying our calculations include:

- Average daily peak period travel on freeway and arterial facilities of 8.0 and 8.6 miles, respectively, per peak period traveler (the average of 439 US urban areas in 2007 – extractable from the data tables accompanying the Urban Mobility Report (UMR) (Schrank and Lomax, 2009).
- About 55% of peak period freeway and arterial travel (by VMT) is congested (the average of 439 US urban areas in 2007 – again from the UMR data tables).
- Average fuel carbon intensity of 8.90 kg CO_2e per gallon; calculated from US Environmental Protection Agency (2009b).
- MOVES-based ESC parameters as shown in Table 1.
- The portion of peak-period travel on uncongested freeways and arterials is assumed to have average speeds of 60 mph and 35 mph, respectively – emissions from travel on local roads is neglected (a conservative assumption for the VBS).
- Induced demand is calculated using mid-point arc elasticity between two travel speed/travel volume conditions $(\bar{v}_1, VMT_1)$ and $(\bar{v}_2, VMT_2)$ as

$$\eta_q^{\bar{v}} = \frac{(VMT_2 - VMT_1)(\bar{v}_2 + \bar{v}_1)}{(VMT_2 + VMT_1)(\bar{v}_2 - \bar{v}_1)}. \tag{15}$$

The net percent emissions changes from CBS (row 3 of the preceding tables) for each facility-pollutant-LOS combination are shown in Fig. 3, again using $\eta_q^{\bar{v}} = 0.3$ and our assumptions. Positive values indicate emissions increases. Fig. 3 shows that the largest emissions reductions from CBS are for heavily congested arterials. NO_x and CO emissions have almost no benefit from freeway congestion mitigation, while HC, the most speed-sensitive pollutant, has generally the highest potential savings.

From the net emissions benefits of CBS shown in Fig. 3, equivalent VBS and DBS are easily determined by their emissions elasticity. For VMT reductions (row 4, Tables 2 and 3), increased fuel efficiency (row 5, Tables 2 and 3), and decreased fuel carbon intensity (row 6, Tables 2 and 3) the emissions point elasticity is −1. Thus, for these strategies a certain percentage

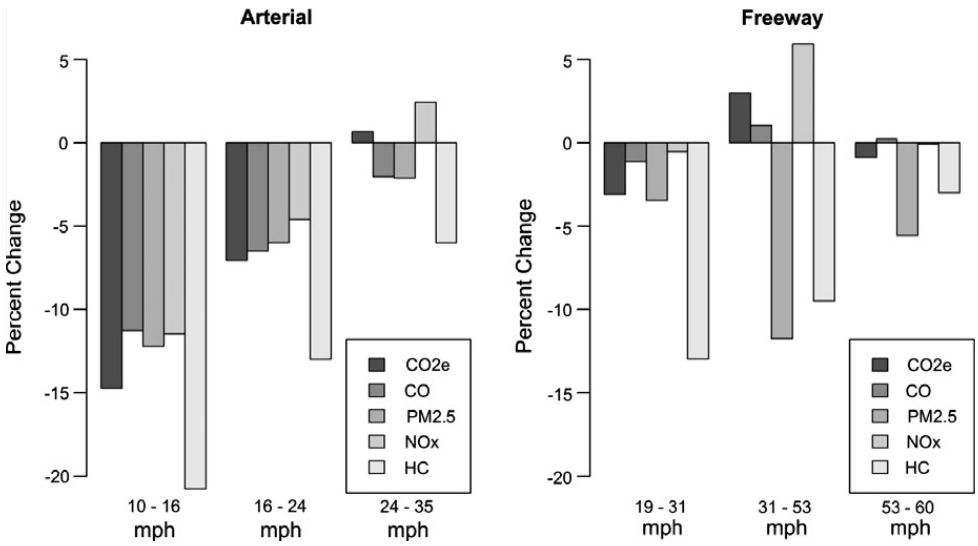

Fig. 3. Percent change in peak period emissions from CBS.

emissions reduction from a CBS can also be accomplished by roughly the same percentage implementation of the VBS or DBS.[3] For example, the 3% reduction in CO_2e for the lowest-speed freeway improvement (Fig. 3) can also be accomplished through a 3% reduction in VMT, a 3% increase in fuel efficiency, or a 3% decrease in fuel carbon intensity.

For EV penetration of the fleet (rows 7 and 8 in Tables 2 and 3) the emissions elasticity is slightly more complicated. Let $J = \{l, h, e\}$ where l and h are entirely ICE classes of LD and HD vehicles and e is a class of LD EV. If all EV are replacing LD ICE vehicles, then $\frac{\partial f_l}{\partial f_e} = -1$ and $\frac{\partial f_h}{\partial f_e} = 0$. The elasticity of E to f_e is then

$$\varepsilon_E^{f_e} = \frac{1}{E}\frac{\partial E}{\partial f_e} = \frac{e_e - e_l}{\bar{e}}. \quad (16)$$

If $e_e = 0$ (zero-emissions EV) and initially $f_e = 0$, then

$$\varepsilon_E^{f_e} = \frac{-1}{1 + f_h\left(\frac{e_h}{e_l} - 1\right)}. \quad (17)$$

The expected range of the ratio $\frac{e_h}{e_l}$ is from around 1 for CO up to 60 for $PM_{2.5}$ at low speeds. Thus, using $f_h = 0.09$, $\varepsilon_E^{f_e}$ can range from -1.0 for CO to -0.16 for $PM_{2.5}$. Considering LCA EV emissions for CO_2e the elasticity is smaller: $\varepsilon_E^{f_e}$ changes by a factor of $\left(1 - \frac{e_e}{e_l}\right)$, or roughly 0.5 employing our assumptions. Since $-1 \leqslant \varepsilon_E^{f_e} < 0$, the emissions elasticity to EV replacement of LD ICE vehicles is equal to or smaller than the emissions elasticity to the other VBS and DBS, and thus greater percent EV penetrations are needed.

Fig. 4 shows the equivalent EV replacement results (i.e. rows 7 and 8 in Tables 2 and 3) for all pollutants on both facilities, again assuming $\eta_q^{\bar{v}} = 0.3$. As expected, the percentages are larger than in Fig. 3 – in addition to having the opposite sign because $-1 \leqslant \varepsilon_E^{f_e} < 0$. From the denominator of Eq. (17), fleets with more HD vehicles (f_h) and pollutants with higher relative emissions rates from HD vehicles $\left(\frac{e_h}{e_l}\right)$ have smaller emissions elasticity to EV penetration, $\varepsilon_E^{f_e}$. Smaller $\varepsilon_E^{f_e}$ means that EV replacement for LD vehicles is less effective at reducing emissions. This effect is reflected in Fig. 4, where $PM_{2.5}$ and NO_x (which have the highest $\frac{e_h}{e_l}$) are proportionally larger than the other pollutants when compared to Fig. 3. The EV replacement of LD vehicles must be particularly large to reduce $PM_{2.5}$ because the $PM_{2.5}$ emissions are primarily from the HD portion of the vehicle fleet. Fig. 4 indicates that VBS that only reduce LD vehicle emissions require large-scale deployment to be competitive with other strategies for reducing certain local pollutants.

7. Vehicle class-specific strategies

The distinct emissions performance of LD and HD vehicles raises the potential for emissions co-benefits from more focused congestion mitigation strategies that address vehicle classes separately. As a comparison of congestion and emissions mitigation approaches and their class-specific effects, Table 4 shows a short list of emissions mitigation strategies with their expected direct impacts on the key variables of this analysis: travel speed v_j, travel volume q_j, emissions rate parameters $a_{i,j}$, and travel demand volume elasticity to speed $\eta_{a_j}^{v_j}$. The cells in the table are filled in with the relationships of an expected increase "+", decrease "–", or no change "o". These relationships are highly generalized, and actual impacts can depend

[3] The percent changes for vehicle efficiency in Tables 2 and 3 are slightly different from the emissions savings because emissions are inversely related to efficiency, so the point elasticity of unity will be different from the arc elasticity which is used in the tables.

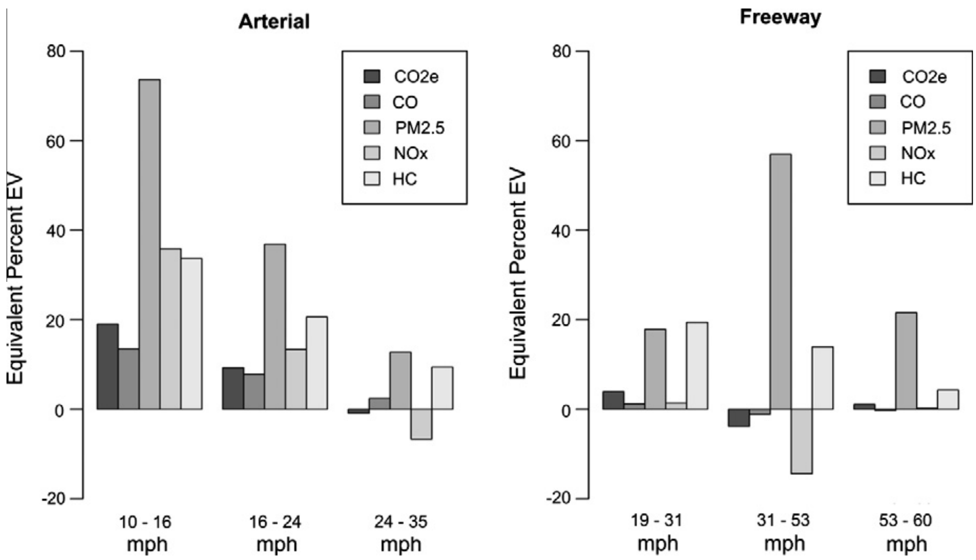

Fig. 4. Zero-emissions LD EV penetration for equivalent VBS.

Table 4
Vehicle class-specific congestion and emissions mitigation strategy impacts.

Mitigation strategy	Light-duty vehicles				Heavy-duty vehicles			
	v_l	q_l	$a_{i,l}$	$\eta_{q_l}^{v_l}$	v_h	q_h	$a_{i,h}$	$\eta_{q_h}^{q_h}$
General capacity increase	+	+	o	o	+	+	o	o
Truck-only lanes (no toll) – new capacity	+	+	o	o	+	+	o	o
Truck-only lanes (no toll) – appropriated capacity	–	–	o	o	+	+	o	o
Truck-only lanes (tolled) – new capacity	+	+	o	o	+	o	o	–
Truck-only lanes (tolled) – appropriated capacity	–	–	o	o	+	o	o	–
Congestion pricing/demand reduction strategies	+	–	o	–	+	–	o	–
Vehicle/fuel efficiency improvements	o	o[a]	–	o	o	o[a]	–	o

[a] Assuming fuel cost savings do not lead to induced travel.

on the details of implementation. Truck-only lanes (TOL) are roadway facilities that provide exclusive right-of-way for HD vehicles (Transportation Research Board, 2010). Just as general capacity expansions can employ road pricing to mitigate induced demand, TOL can utilize lane pricing (tolling) for the same purpose.

Capacity expansions (CBS) increase v_l and q_j, and the emissions effect depends on the relative magnitude of each as demonstrated. The impacts of TOL on LD vehicles depend on whether the TOL are added capacity (in which case v_l and q_l would likely increase with the relocation of HD vehicles), or the TOL are appropriated general purpose capacity (in which case the capacity decrease for LD vehicles would likely lower v_l and q_l, though traffic flow impacts of this type of TOL vary (Transportation Research Board, 2010)). A tolled TOL can have similar efficiency benefits without an increase in q_h by offsetting travel time-savings with toll costs; i.e. reducing the effective value of $\eta_{q_h}^{v_h}$.

Congestion pricing and other forms of DBS reduce effective demand elasticity to travel speed, $\eta_{a_j}^{v_j}$ - but can also increase v_j by decreasing q_j and so reduce e_j. VBS include improvements in vehicle and fuel efficiency that reduce e_j by reducing the ESC parameters $a_{i,j}$, with the only likely impact on q_j or v_j being possible induced demand through a rebound effect due to decreased travel costs. The net effect of any of the strategies in Table 4 on emissions can be determined by the joint evaluation of $\varepsilon_{e_j}^{v_j}$ and $\eta_{a_j}^{v_j}$, representing tradeoffs between vehicle efficiency and volume.

8. Conclusions

We find that congestion mitigation does not inevitably lead to reduced emissions, and that the net effect of congestion mitigation will greatly depend on the type of emissions being analyzed. In the long run, capacity-based congestion reductions within certain speed intervals (e.g. 30–40 mph) can be expected to increase emissions of CO_2e, CO, and NO_x through increased vehicle travel volume. Wider speed ranges will see increased emissions in more specific conditions. Vehicle emissions of HC and $PM_{2.5}$ have greater potential for reductions through traffic congestion mitigation than CO_2e, CO, or NO_x.

Fleet composition and vehicle class relative emissions rates are also key factors that impact congestion and emissions mitigation strategies. Reducing light-duty vehicle emissions alone has only a small impact on $PM_{2.5}$; and a limited impact on other pollutants. Emissions reduction strategies must also seek efficiency improvements for heavy-duty vehicles. Further, even as a small fraction of the vehicle fleet, the demand elasticity of heavy-duty vehicles is important for predicting the emissions effects of general congestion mitigation. Advanced-efficiency vehicles with emissions rates that are less sensitive to congestion than conventional vehicles generate less emissions co-benefits from congestion mitigation strategies.

Applying hypothetical level-of-service improvements reveals that large percentage speed increases lead to comparatively small or non-existent net reductions in emissions. The largest potential emissions reductions for all pollutants are on heavily congested arterials; on freeways, large potential reductions are only seen for HC and $PM_{2.5}$ emissions. Comparing these capacity-based mitigation strategies with alternative approaches indicates that the same or more emissions benefits can be achieved by demand or vehicle based emissions reduction strategies.

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