

# **Impacts of Traffic Operations Strategies on Passenger Vehicle Use and Greenhouse Gas Emissions**

## **Technical Background Document**

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Policy Brief: [http://www.arb.ca.gov/cc/sb375/policies/tsm/tos\\_brief.pdf](http://www.arb.ca.gov/cc/sb375/policies/tsm/tos_brief.pdf)

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### **Study Selection**

The history of research on traffic operations strategies dates back to the late 1950s and focused on the potential of such strategies to reduce traffic delay (De Coensel et al., 2012). Included in this body of work are studies of strategies to manage congestion and speed on freeways, as well as signal coordination strategies on local streets. Not until recently have traffic operations strategies been evaluated for their potential to reduce greenhouse gas (GHG) emissions.

This review includes studies in peer-reviewed journals and conference proceedings that estimate the effects of traffic operations strategies on GHG emissions or on fuel use if GHG emissions are not reported (Table 1). The review includes studies from the U.S. as well as international studies, given the scarcity of the former. Four of the selected studies examine traffic signal coordination strategies for local streets (Madireddy et al., 2011; Stevanovic et al., 2009; Zhang et al., 2009; Midenet et al., 2004). Three studies examine incident response programs on freeways with respect to incident clearance times (Avetisyan et al., 2014; Fries et al., 2007; Fries et al., 2012). One study examines the effect of freeway ramp metering, taking into account flow in the freeway mainlanes and on the metered ramp, as well as the diversion of some vehicles to another route to avoid the metered ramps (Bae et al., 2012). Two studies examine speed control strategies that reduce average travel speeds on freeways (Barth and Boriboonsomsin, 2008; Madireddy et al., 2011). Studies of hypothetical traffic operations strategies were excluded (e.g. Stathopoulos and Noland, 2003; De Coensel et al., 2012; Zegeye et al., 2010).

### **Methodological Considerations**

Ideally, the effects of traffic operations strategies would be evaluated using controlled field experiments in which vehicle emissions data were collected before and after the implementation of the strategy on the affected roadway segment (the “treatment” site) and on a comparable roadway segment not affected by the implementation of the strategy (a “control” site). Such experiments are extremely challenging to design and

expensive to implement (De Coensel et al., 2012). Key challenges and/or costs include identifying equivalent treatment and control sites, recruiting drivers at those sites, equipping vehicles with emission and vehicle operation measurement systems, and conducting the experiment over a long enough time period to capture secondary effects. Because of these challenges, most studies use microsimulation traffic models together with modal emissions models to estimate the effects on GHG emissions of traffic operations strategies. These models, described below, have become widely available within the last 10 years and are generally considered to produce realistic results (De Coensel et al., 2012; Madireddy et al., 2011).

In general, the estimation of the effects of traffic operations strategies on GHG emissions involves two sequential components. First, the effects of the strategy on vehicle activity (in terms of speed, acceleration, deceleration, etc.) on the affected segment(s) of roadway for a defined period of time are estimated with and without the strategy in place. Second, the emissions associated with this vehicle activity are estimated for the entire fleet of vehicles using the segment(s) of roadway for that period of time. The impact of the strategy is then estimated as the difference in emissions between the “with strategy” and “without strategy” scenarios. The methods for these components differ among the studies evaluated (Table 2).

All of the studies included in this review except for Barth and Boriboonsomsin (2008) and Midenet et al. (2004) use microscopic traffic models or vehicle activity models to simulate vehicle activity on the roadway segment(s) affected by the traffic operations strategy with and without the strategy in place. Microscopic traffic models simulate the temporal and spatial activity of vehicles by modeling individual vehicles on a roadway following empirically derived rules of driver and vehicle behavior. These models are able to represent the effect of stop-and-go traffic on vehicle starts, idling, speed, acceleration, and deceleration activities by location on a second-by-second basis. They require detailed data on the roadway network, vehicle fleet, and traffic flows, and they are computationally intensive. As a result, they are typically applied to portions of the network (e.g., an intersection, road, or corridor) rather than to the entire regional network. The models are also capable of representing the effect of roadway grade and driver attributes (e.g., aggressive or not) that are known to significantly impact vehicle emissions (Pandian et al., 2009). These models can be used with default values based on available data or be calibrated and validated with local data.

The two studies that did not use microscopic traffic models obtained vehicle activity data measured directly from the field. Barth and Boriboonsomsin (2008) use data from the California Performance Measurement System (PeMS)—a system of freeway sensors that spans all major metropolitan areas in California and measures volume of traffic by

location and time from which average speeds can be calculated. Midenet et al. (2004) determine vehicle activity using video-based traffic measurement, which captures second-by-second visual data that is translated into vehicle activity data by specially designed algorithms.

Emissions models are then applied to vehicle activity data from field measurements or microscopic traffic models to estimate GHG emissions. All except three studies (Fries et al., 2007; Fries et al., 2012; Bae et al., 2012) use modal emissions models that account for the mode of operation of specific vehicles and their activities (speed, acceleration, deceleration, idling, etc.) on specific roadway segments to estimate GHG emissions with and without the strategy. These emissions models apply emissions rates that correspond to second-by-second vehicle activity for specific characteristics of vehicles. These data are frequently collected both through on-road vehicle measurements and in laboratory settings. Some studies adjust these models to reflect the local vehicle fleet rather than the fleet for a larger geographic area (Madireddy et al., 2011; Stevanovic et al., 2009; Zhang et al., 2009; Avetisyan et al., 2014). Three studies use non-modal emissions models with volumes and average speeds from a microscopic traffic model with local fleet mix and traffic data for a given time period and location (Fries et al., 2007; Fries et al., 2012; Bae et al., 2012).

Generalizing findings across studies is challenging. Most studies do not provide details about the fleet composition used in the analysis, beyond stating that it is representative of a particular fleet in a geographic area (De Counsel et al., 2012). Typically, when vehicle activity and emissions measurements are actually sampled from the network as part of a study, only a limited number of vehicles types (and thus a non-representative sample) are used (Madireddy et al., 2011; Zhang et al., 2009). This is an important limitation given that research shows that traffic operations strategies may only yield modest benefits in areas with relatively fuel-efficient fleets compared to areas with inefficient fleets (Stathopoulos and Noland, 2003; Noland and Quddus, 2006; Bigazzi and Figliozzi, 2012).

In addition, estimated effect sizes vary based on the share of vehicles on a segment that are actually affected by the traffic operations strategy during a specific time period; this share can vary by the time period, size of the network, and vehicle throughput (see Table 2). Some studies use a limited number of test vehicle runs with monitoring equipment to measure emissions before and after, or at a treatment and control site (i.e., Madireddy et al., 2011; Zhang et al., 2009). However, measurements from a limited number of drivers and vehicles cannot be reliably generalized to the fleet. This is largely due to the fact that driving styles are known to have a large effect on vehicle emissions (Pandian et al., 2009).

Four studies use a suburb-to-city corridor as the study unit of analysis (Madireddy et al., 2011; Stevanovic et al., 2009; Barth and Boriboonsomsin, 2008; Avetisyan et al., 2014). The remaining studies use either a freeway/highway segment (Stathopoulos and Noland, 2003; Zegeye et al., 2010; Fries et al., 2007; Fries et al., 2012), road segment (Zhang et al., 2009; Stathopoulos and Noland, 2003), or intersection (De Coensel et al., 2012). The studies also use different times of day, including: the one-hour am and pm peak (Midenet et al., 2004; Stathopoulos and Noland, 2003; Madireddy et al., 2011; Woldeab et al., 2014); pm peak periods of two to three hours (Stevanovic et al., 2009; De Coensel et al., 2012; Bae et al., 2012; Avetisyan et al., 2014); off-peak periods (Barth and Boriboonsomsin, 2008); and 24-hour periods (Fries et al., 2007; Fries et al., 2012). Due to the computational intensity of microsimulation traffic and emissions models, it is also difficult to estimate overall effect of traffic operations strategies over larger geographic areas and longer periods of time.

In addition, with the exception of the speed control strategies, these traffic operations strategies decrease traffic delay and thus enhance the effective capacity of the roadway. These improvements may thus induce additional trips, divert travel from other routes, and increase trip lengths. A limited number of studies address the effects of induced travel (Stathopoulos and Noland, 2003; Noland and Quddus, 2006; Bigazzi and Figliozzi, 2012) and find that GHG emissions reductions from smoother traffic flow and less congestion may be entirely offset by induced travel effects (see the Policy Brief on Highway Capacity and Induced Travel at <http://arb.ca.gov/cc/sb375/policies/policies.htm>). Only one study included in the Policy Brief on the Impacts of Traffic Operations Strategies on Passenger Vehicle Use and Greenhouse Gas Emissions that accompanies this Technical Background Document accounted for the effect of induced travel (Zhang et al., 2009). Studies that do not account for induced travel effects likely overestimate the effects of these strategies on GHG emissions. In contrast, speed control strategies may discourage travel by increasing travel times, in which case the effects on GHG emissions may be underestimated.

Table 1: Summary of Study Designs

	Study	Location	Strategy Description	Out- come	Time of day	Traffic Volume (1000s)	Unit of Analysis
Signal Coordination	Madireddy et al., 2011	Antwerp, Belgium	With and without actual traffic signal coordination	CO <sub>2</sub>	AM peak hour	0.7 - 1	Suburb to city corridor
	Stevanovic et al., 2009	Salt Lake City, Utah, U.S.	Optimize signal coordination to reduce fuel use, CO <sub>2</sub> , and delay	CO <sub>2</sub>	PM peak (4-6)	8	Suburb to city corridor
	Zhang et al., 2009	Beijing, China	With and without signal coordination	CO <sub>2</sub>	AM peak (9-11)	NA	Road
	Midenet et al., 2004	Paris suburb, France	With current signal coordination and with adaptive real-time coordination (randomly vary programs over time during data collection period)	CO <sub>2</sub>	Daily peak hour	3	Intersection
Traffic Incident	Avetisyan et al., 2014	Montgomery County, Maryland, U.S.	Lane blockages	CO <sub>2</sub>	AM peak (6 -9)	29	Suburb to city corridor (7 mi.)
	Fries et al., 2007	South Carolina, U.S.	Incidence clearance time with and without program (local historical data)	Fuel	Daily	-	5 freeway sites (for a total of 48 miles and 31 interchanges)
	Fries et al., 2012	South Carolina, U.S.	Incidence clearance time with and without program (local historical data)	Fuel	Daily	-	Freeway section (11 mi.) with 8 interchanges
Ramp Meter	Bae et al., 2012	Korea	Reduce congestion on mainline, increase stop and go on ramp meter, and increase meter detour travel	CO <sub>2</sub>	PM peak (7-8)	2.6	Highway connecting to city (3 ramps) with detour routes
Speed Control	Barth & Boriboonsomsin, 2008	Southern CA, U.S.	Reduce the 1/3 of VMT traveling at $\geq 75$ mph to 60 mph (using unspecified speed enforcement strategies)	CO <sub>2</sub>	Off-peak (11 pm to 12 am)	NA	SR-60 (Inland Empire to LA)
	Madireddy et al., 2011	Antwerp, Belgium	Reduce speeds from 100 to 70 km/h on freeway, 70 to 50 km/h on major road & 50 to 30 km/h on major arterial & residential roads	CO <sub>2</sub>	AM peak hour	0.7 - 1	Suburb to city corridor

Table 2: Summary of Study Methods and Data

	Study	Traffic and Emissions Models	Traffic Data	Vehicle Activity Estimation	Fleet Composition	CO <sub>2</sub> or fuel use Estimation
Signal Coordination	Madireddy et al., 2011	PARAMICS +VERSIT+	Speed, acceleration, throttle position, fuel, CO <sub>2</sub> from 4 diesel vehicles	Microscopic traffic model	12,500 vehicles of different vehicle characteristics	Modal emissions by vehicle activity and type
	Stevanovic et al., 2009	VISSIM+ CHEM	Turning-movement, counts, saturation flows, intersection, speed, vehicle type counts and times	Microscopic traffic model	CHEM US vehicle fleet (excluding trucks before 1998 & after 2002) adjusted with field vehicle type data	Modal emissions by vehicle activity and type
	Zhang et al., 2009	VISSIM+ CHEM	Composition, road condition, flow, # vehicles entering & exiting intersections; 1 vehicle for 2 days	Microscopic traffic model	Default weighted by car, light duty vehicles and bus to reflect local conditions	Modal emissions by vehicle activity and type
	Midenet et al., 2004	Data 7/98-2/99	Video- measures by second: queue lengths, # stopped vehicles, and flow	Microscopic traffic model	Representative sample of European Union fleet	Modal emissions by vehicle activity and type
Traffic Incident	Avetisyan et al., 2014	VISSIM+ ORSEEM	Travel time & volume includes diverted travel	Microscopic traffic model	Representative sample of county registered vehicles	Modal emissions by vehicle activity and type
	Fries et al., 2007	PARAMICS +MOBILE6	Volumes, travel times, queue lengths and driver behavior	Microscopic traffic model	3 vehicle types with weight categories for heavy duty based on state registered vehicles	Fuel consumption rates (from general sources) for 14 speeds and idling
	Fries et al., 2012	PARAMICS +MOBILE6	Same as above	Microscopic traffic model	Same as above	Same as above
Ramp Meter	Bae et al., 2012	TSIS	Traffic volumes; stated preference survey for detours	Mean speeds and volume from microscopic traffic model	Type (small, medium, & large) by fuel (gasoline, diesel and LPG) by speed (> or < 65.4 Km/h)	Fixed CO <sub>2</sub> factors applied to vehicle activity data
Speed Control	Barth & Bori-boonsin, 2008	CHEM	Cross-sectional PeMs' flow, speed, and density data (3 weeks, 2007)	Mean speeds and volumes	Mean Southern California fleet	Modal emissions for mean fleet speed
	Madireddy et al., 2011	PARAMICS +VERSIT+	Speed, acceleration, throttle position, fuel use & CO <sub>2</sub> from 4 vehicles	Microscopic traffic model	12,500 vehicles of different vehicle characteristics	Modal emissions by vehicle activity and type

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