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Vehicle emissions in congestion: Comparison of work zone, rush hour and free-flow conditions

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ABSTRACT

Traffic congestion frequently occurs during rush hour periods and in work zones, and can account for a significant share of vehicle emissions and air quality impacts. This study estimates vehicle emissions from light- and heavy-duty vehicles (LDVs, HDVs) in work zone and rush hour congestion, which are compared to emissions under free-flow traffic conditions. Field experiments collected second-by-second vehicle speed and acceleration data on typical weekdays along a freeway segment that experienced both rush hour and work zone congestion. The collected data were smoothed and used in the Comprehensive Modal Emissions Model (CMEM) to generate second-by-second emissions. For LDVs and when expressed as g mi^{-1} vehicle^{-1}, the highest emission rates of hydrocarbons (HC), carbon monoxide (CO) and nitrogen oxide (NO_x) occurred during the transitional period when traffic changed from free-flow to congested conditions and vice-versa; the lowest rates occurred during low speed work zone congestion periods. However, the highest fuel consumption rates and the highest carbon dioxide (CO_2) emissions occurred under work zone congestion, while the lowest fuel consumption and CO_2 emissions occurred with rush hour congestion. On a link or emission density basis (e.g., g mi^{-1} s^{-1}), rush hour congestion had the highest emission and fuel consumption rates. Results for HDVs differed in that work zone congestion was associated with the highest emissions of HC, CO and CO_2, and the highest fuel consumption, while NO_x emission rates under the different traffic conditions were similar. On an emission density basis, however, the rush hour congestion again was associated with the highest emissions of CO, NO_x and CO_2 (but not HC). The differences between congestion and free-flow conditions highlight the importance of accounting for congestion in emission, exposure and health risk evaluations, as well as transportation planning.
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1. Introduction

Increased traffic in urban transportation networks in recent years has led to widespread traffic congestion, which is now nearly ubiquitous in many urban areas (Schrank and Lomax, 2007; World Bank, 2006). Since 1980, for example, urban vehicle-miles traveled (VMT) in the U.S. grew 40% faster than urban capacity (BTS, 2006). Such growth in traffic, and the congestion that it causes, not only affects the mobility of travelers, but also may increase vehicle emissions of carbon monoxide (CO), carbon dioxide (CO_2), volatile organic compounds (VOCs) or hydrocarbons (HCs), nitrogen oxides (NO_x), particulate matter (PM), and other pollutants associated with vehicles. Emissions may increase as vehicles spend more time in congestion, idling or crawling, and undergoing numerous acceleration and deceleration events. Although emissions under congested conditions have been previously examined using experimental and modeling approaches, information regarding the effects of congestion type on emissions (e.g., work zone versus rush hour) remains limited, as noted in the background section of this paper.

Vehicles are the dominant source of many air pollutant emissions in urban areas (TRB, 2002), and congestion has the potential to significantly worsen ambient air quality, particularly near major roadways. Impacts due to vehicle emissions have been receiving increasing attention, and recent epidemiological studies show elevated risks of non-allergic respiratory morbidity, cardiovascular morbidity, cancer, allergic illnesses, adverse pregnancy and birth outcomes, and diminished male fertility for drivers, commuters and individuals living near roadways (WHO, 2005). For a typical working adult, we previously have estimated that a 30 min day^{-1} travel delay accounts for 21 ± 12% of the total daily benzene exposure and 14 ± 8% of $PM_{2.5}$ exposure (Zhang and Batterman, 2009). Means to reduce congestion-related impacts on exposures and health risks are being investigated, including congestion pricing and traffic controls. As examples: congestion pricing in center city

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Stockholm is estimated to avoid 20–25 deaths annually in the inner city and 25–30 deaths annually in the metropolitan area (Eliasson et al., 2009); such pricing in London is predicted to gain 183 years of life per 100,000 population in the congestion charging zone, and ten times that in the greater London area (Tonne et al., 2008).

The aim of this paper is to investigate effects of congestion on vehicle emissions and fuel consumption. We present results of a field study that measured second-by-second speeds on a highway segment subject to congestion from both work zone and rush hour traffic. After providing background on traffic congestion and vehicle emissions, we describe the field study design, emission models, and the data analysis methods. The results and discussion present the measured speed and acceleration data, predicted emission rates from the Comprehensive Modal Emissions Model (CMEM) as well as a standard constant-speed emission model, the application of these models in several case studies, and a sensitivity analysis. The conclusions summarize results and suggest further research needs.

2. Background

2.1. Traffic congestion and emissions

Pollutant emissions that occur during congestion periods, especially from work zone activities such as lane closures, have received limited attention. A few studies have been conducted. Sjodin et al. (1998) showed up to 4-, 3- and 2-fold increases in CO, HC and NO_x emissions, respectively, with congestion (average speed = 13 mph) compared to uncongested conditions (38–44 mph). De Vlieger et al. (2000) indicated that CO, HC and NO_x emissions and fuel consumption rates of passenger cars during rush hour increased 10%, 10%, 20% and 10%, respectively, compared to smooth flow conditions, and that changes in emission and fuel consumption rates varied by vehicle and road type. Frey et al. (2001) used on-board measurements of CO, NO and HC, and found a 50% increase in emissions during congestion. In dynamometer tests using a driving cycle with more acceleration and a higher average speed than the U.S. EPA's standard Federal Test Procedure (FTP), CO, HC and NO_x emissions exceeded FTP results by factors of 4, 2 and 2, respectively (Department of Transport and Regional Services, 2001). Anderson et al. (1996) found that congestion increased CO, HC and NO_x emissions by 71%, 53% and 4%, respectively, compared to free-flow conditions. Bushman et al. (2008) estimated CO, NO_x and HC emissions rates for cars and trucks due to work zone travel delay. Kendall (2004) used a traffic model (Kentucky User Cost Program version 1.0, KyUCP) to estimate the average speed in work zones, which then was used to estimate emissions using the Motor Vehicle Emissions Factor Model version 6.2 (MOBILE6.2). However, the emission factors in MOBILE6.2 incompletely represent work zone conditions, which include periods of acceleration, deceleration and idling, as well as some medium speeds. Overall, the available field study measurements suggest that congestion elevates vehicle emissions, however, there is considerable uncertainty in quantifying these changes, as a result of limited testing, differences among vehicles, and varying traffic conditions.

Emission models based on average vehicle speeds do not explicitly account for congestion since they do not incorporate input parameters that describe the presence or nature of congestion (Smit et al., 2008). Models based on actual driving patterns, e.g., using instantaneous speed and acceleration/deceleration profiles as inputs, can account for congestion and local conditions. Traffic micro-simulation has become more popular in the recent years since activities of individual vehicles can be simulated at fine time scales (e.g., every second). Modern computers now allow micro-simulation of even very large road networks, e.g., a micro-simulation model has been applied to the greater Toronto area (Hao et al., 2010), and traffic simulations have been used to estimate emissions of past congested conditions (Cappiello, 2002; Lee et al., 2009; Hao et al., 2010). (Details of several modeling approaches are described in following sections.)

The lack of consistency among publications regarding congestion-related emissions is an important gap in our understanding of vehicle emissions, especially given the growing frequency and severity of congestion. The relationship between congestion and vehicle emissions is complex (TRB, 2002), and the studies just discussed show considerable variability. It is clear that improvements in fuels and vehicles, such as low sulfur fuels and 3-way catalytic converters, have substantially reduced emissions on an individual vehicle basis. Emission rates depend on vehicle characteristics (e.g., model year, engine, fuel type, and maintenance) and the distributions of speed and acceleration, which in turn depend on road type, traffic flow and other factors (TRB, 2002). In congestion, driving patterns are altered, and the norm in stop-and-go traffic is frequent acceleration and deceleration (Cappiello, 2002; Smit, 2006; TRB, 2002). Modern gasoline engines operate close to stoichiometric conditions at low and medium loads, but engines operate in a fuel-rich mode under hard acceleration, which can increase HC and CO emissions even with the presence of a catalytic converter (Alkidas, 2007). NO_x emissions are less likely affected since these are highest under high temperatures and fuel-lean modes (TRB, 1995). Emissions of PM and HCs can increase under deceleration due to the presence of unburned fuel (Cappiello, 2002).

2.2. Emission modeling

Vehicle emissions are most commonly estimated using "macroscopic" emission models, such as MOBILE6.2, that are based on standardized driving cycles intended to represent typical driving patterns along major types of roads (e.g., freeways, arterials, ramps, and local roads; EPA, 2003; Pierce et al., 2008). Pollutant emissions are estimated from measurements on test vehicles subjected to specific driving cycles, as simulated on a chassis dynamometer. Emissions associated with specific traffic conditions are then derived by accounting for differences between the desired average traffic speed and other environmental parameters, and those associated with the standardized driving cycle. MOBILE6.2 and other macroscopic models are widely used in emission inventory and other regional applications. However, the use of such models to estimate emissions for specific roadways has been criticized since they do not consider the full range of driving patterns that may be encountered (Joumard et al., 2000). Since emission rates are based on an average speed in fixed driving cycles, there is only limited ability to consider alternate driving patterns. While different driving cycles can produce identical average speeds, emissions depend strongly on the specific acceleration and deceleration patterns. Thus, actual emissions can be significantly underestimated since acceleration, deceleration and aggressive driving patterns are not fully represented (Joumard et al., 2000). Emissions during idling also requires better quantification, especially considering the time spent in – or near – this condition during congestion. Currently, MOBILE6 does not use results of idling tests, and idling results are based on emission rates measured at a speed of 2.5 mph. The real-world accuracy of this approach is unknown. Overall, macroscopic models may inaccurately estimate emissions associated with congestion for specific road segments and traffic conditions (Smit et al., 2008).

"Microscopic" models provide an alternative and in some ways an ideal approach to estimate vehicle emissions in congestion and other driving conditions. Models such as the Comprehensive Modal Emissions Model (CMEM; Scora and Barth, 2006) and the new EPA

Motor Vehicle Emission Simulator (MOVES; EPA, 2009) can estimate emissions for temporal scales ranging from second to hours, and for specific vehicles as well as vehicle fleets. These models explicitly account for idling, accelerating, cruising and decelerating engine operating conditions, and can simulate second-by-second speed and power fluctuations of vehicles on a road network. Temporal and vehicular aggregations are necessary since these models are designed to predict emissions for vehicle categories (Scora and Barth, 2006). These models can be applied to both conventional and greenhouse pollutants, and have been used to model impacts of traffic congestion (Barth and Boriboonsomsin, 2008). On the downside, microscopic models tend to be data and computationally intensive when modeling large areas with complex road networks, although small road networks can be easily simulated using modern computers.

3. Methods

3.1. Field study

Instantaneous traffic speed and position data were collected on a 5 mile segment of Interstate 94 in Ann Arbor, Michigan, selected for both convenience and because it had a nearby permanent traffic recorder (PTR) operated by the Michigan Department of Transportation (MDOT; Fig. 1). The portion of the segment west of US-23 had two lanes in each direction; the segment east of US-23 had three lanes in each direction. The east- and west-bound annual average daily traffic (AADT) volumes for these segments were 78,300 and 91,300 vehicles day^{-1}, respectively; the commercial average daily traffic (CADT) volumes were 8000 and 8900 vehicles day^{-1} (MDOT, 2008). Heavy diesel trucks accounted for nearly 10% of the total traffic. The east-bound traffic volumes measured during the field study averaged 3099, 2153 and 4040 vehicles hr^{-1} (vph) during morning, midday and evening periods, respectively (work zone period excluded). The posted speed limits are 70 mph for passenger and 60 mph for trucks. On two study days (Sept. 24 and 25, 2008), one east-bound lane was closed from 9 am to 3 pm for road maintenance, leaving two lanes merging to one just west of US-23, and then two lanes (rather than three) just east of US-23. The resulting work zone congestion lowered average speeds from 70 mph for cars and 63 mph for trucks to 21 mph; east-bound traffic volumes decreased only slightly, from 2153 to 1961 vph.

Data were collected on Tuesdays, Wednesdays and Thursdays to better reflect weekday traffic patterns and to avoid weekend effects. Three consecutive weeks in fall 2008 were studied: September 16–18; September 23–25; and September 30–October 2. Data were collected during morning (7:00–9:00) and evening rush hour periods (16:00–18:00), and a midday comparison period (11:00–13:00). Data were collected on a total of 9 days representing a total of 54 h. Speed and acceleration data were collected by repeatedly driving a vehicle back and forth on the freeway segment using the “floating car” technique, which is frequently used in traffic studies for this purpose (Dion, 2007). The protocol involves passing as many vehicles as those that passed the test vehicle. Given that behaviors of cars and (large) trucks can differ significantly, separate profiles were obtained for cars and trucks by following them separately. In each 2-h study period, the test vehicle typically made 5–9 runs along the segment and covered 34–63 miles, depending on the time of day and the amount of congestion encountered.

Two test cars were used: a 2001 Ford Taurus with 25,000 miles (weeks 1 and 2); and a 2005 Ford Taurus four-door sedan with 40,000 miles (week 3). Both were rented from the University of Michigan's fleet and were in good operating condition. Vehicle speed and location were determined every 1 s using a GPS unit (GPS18 USB receiver, Garmin Inc., Olathe, Kansas, US) placed on the car's roof to improve signal quality. For 95% of cases, GPS accuracy was within 3 m. The receiver was linked to a laptop via Garmin nRoute software, which stored speed profiles and location information on a second-by-second basis.

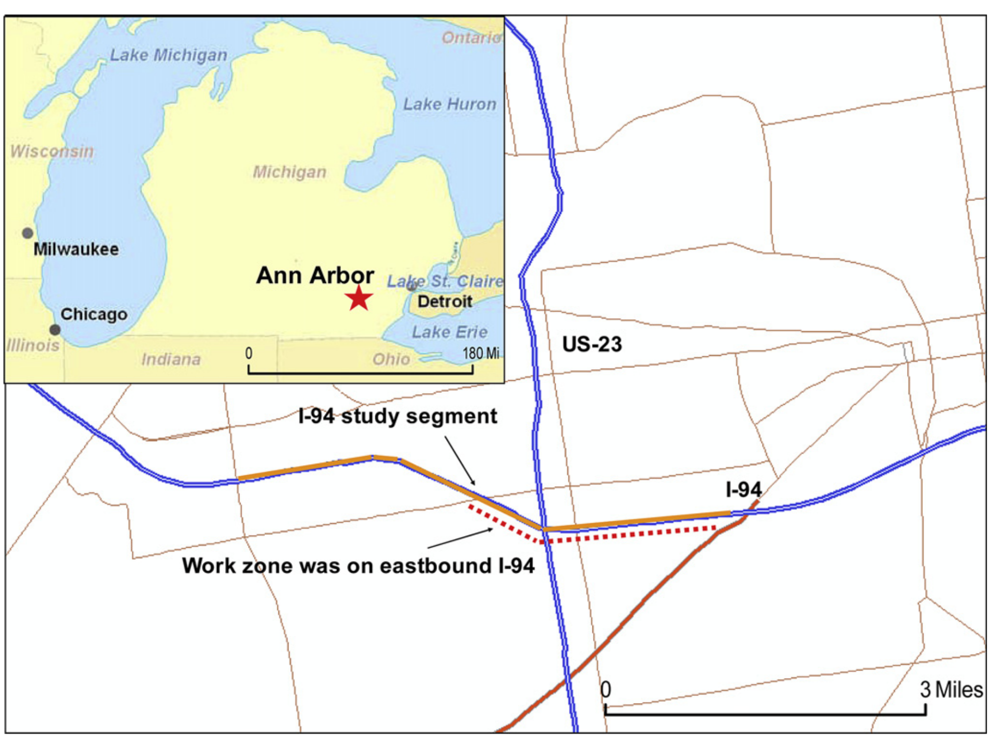

Fig. 1. Map of study area and study segment for field study, shown in orange. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

3.2. CMEM emission modeling and response surface analyses

The microscopic model used in this research, the Comprehensive Modal Emissions Model (CMEM), is a physically-based, power-demand model (Scora and Barth, 2006). The latest version of the model (version 3.0) predicts fuel consumption and emissions of CO, HC, NO_x and CO_2 for different modes of vehicle operation, e.g., idle, cruise, acceleration and deceleration, and includes two similarly structured sub-models for light-duty vehicles (LDVs) and heavy-duty diesel vehicles (HDVs). Each sub-model is composed of six modules: engine power demand, engine speed, air/fuel ratio for LDVs or engine control unit for HDVs, fuel rate, engine-out emissions, and catalyst pass fraction for LDVs or after-treatment pass fraction for HDVs. CMEM has been calibrated using data from the National Cooperative Highway Research Program, which includes both engine-out and tailpipe emissions of CO, HC, NO_x and CO_2 for over 400 vehicles in 35 vehicle/technology categories. The model's inputs include traffic composition, vehicle and operation variables, e.g., speed, acceleration and road grade, and model-calibrated parameters, e.g., cold start coefficients and engine friction.

To show the sensitivity of CMEM to inputs, CMEM predictions for all possible speed and acceleration combinations were visualized using a response surface analysis (also called an emission map). Emissions were predicted over an evenly spaced grid of 80 speed categories (1–80 mph, every 1 mph) and 81 deceleration/acceleration classes (−4 to 4 mph s^{-1}, every 0.1 mph s^{-1}). Contour plots of the resulting emission factors were generated using R 2.7.2 (R Development Core Team, 2006) and Matlab 7.8 (R2009a, MathWorks, Inc., Natick, MA).

3.3. Emission estimates for the case study

Link-based emissions, defined as emissions per distance traveled, were estimated for cruise, congestion and other traffic flow conditions using the second-by-second field data. This analysis was restricted to the 147 east-bound trips measured on I-94 because only trips in this direction experienced both work zone and rush hour congestion. Emissions were estimated as follows: (1) Vehicle speed and position data collected on the initial and the final 800 m portions of the segment were excluded to avoid ramp effects given that our primary goal was to capture speed/acceleration profiles on the freeway. (2) Speed and position data were checked to identify errors and outliers using criteria proposed by Dion (2007), who defined valid ranges for acceleration or deceleration for various speed intervals, and replacing any errors or outliers detected by linear interpolations. (3) Observed speeds were smoothed using 3 s equal-weight moving averages (Dion, 2007), a step taken because GPS data can includes errors, e.g., signal loss and poor electrical contact between the receiver and the laptop. (4) Acceleration/deceleration was calculated as the difference between adjacent speed values in successive 1s intervals. (5) Speed/acceleration profiles for each trip were aggregated for analysis. Initially, profiles were grouped by trip average speed, followed vehicle type (LDV or HDV), and time of day (morning, midday, afternoon), giving 21 categories (shown in Supplemental Table 1). We analyzed emission rates for each speed bin, and then, according to the variations among different speed bins, further aggregated results by vehicle type and four traffic conditions that were primarily indicated by the average trip speed: speeds exceeding 65 mph for LDV and 60 mph for HDV were considered as free-flow conditions; speeds just below the speed threshold (60–65 mph for LDVs, 55–6 mph for HDVs) were considered as transitional conditions; speeds well below the speed threshold (50–60 mph for LDVs, 39–55 mph for HDVs) and occurring during peak commuting times were considered as rush hour congestion; and lane closures resulting in low speeds (15–25 mph for both LDVs and HDVs) were considered as work zone congestion. (6) Descriptive statistics of speed and acceleration were calculated for each grouping. (7) Emissions for each category were calculated in CMEM simulations using the second-by-second speed and acceleration data.

For further analysis of the speed/acceleration profiles, we calculated and plotted the joint probability distribution of the second-by-second speed and acceleration data using 1 mph speed bins (0–80 mph) and 0.1 mph s^{-1} acceleration bins (−4 to 4 mph s^{-1}) in seven groups: LDVs and HDVs separately in the morning, midday and evening periods; and LDVs and HDVs together in one additional group during the work zone periods.

We also evaluated an alternate and possibly simpler approach to estimate emissions, which also provided insight into the speed/acceleration–emissions relationship. Link emissions were estimated using the joint probability matrix representing the speed and acceleration data, which was multiplied by the CMEM response surface matrix representing CMEM outputs, and then divided by total travel miles. These calculations were performed for each vehicle class, and then the result was summed, weighted by the number vehicles in each class. This approach is demonstrated for selected scenarios, e.g., 70–75 mph speed range for LDVs at midday. This method has two potential advantages. First, it is computationally efficient since CMEM simulations are not needed once the CMEM response surface matrix is obtained (this surface can be used with different joint probability matrices). Second, results are easily visualized and show which speed-acceleration combinations are associated with high emissions. However, as compared to running CMEM directly, errors may be introduced since the joint probability and response surface matrixes are calculated at a finite number of speed and acceleration combinations (binning error), and since the approach does not account for the vehicles' previous operating conditions (memory error).

A sensitivity analysis was conducted to examine the effect of averaging time (or smoothing) for the speed/acceleration data. This analysis simulated emissions in two speed ranges for both LDVs (20–25 and 70–75 mph, both at midday) and HDVs (20–25 and 60–65 mph, again at midday). Running averages using 1, 2, 3, 5, 10, 50, 100 and 500 s periods were derived from the original cleaned and imputed data (without smoothing). Emissions were estimated using CMEM simulations for each averaging time.

The link-based emission density (g mi^{-1} s^{-1}), an indicator relevant to predicting near-road concentrations, was estimated using CMEM estimates for free-flow, rush hour and work zone conditions as the product of emission factors (g mi^{-1} $vehicle^{-1}$) and traffic volumes (vehicles s^{-1}). We grouped both transitional and rush hour congestion periods into the rush hour period to obtain values typical of rush hour periods, e.g., 4–6 pm. The calculation used estimated emission rates for LDVs and HDVs in this study and the time-specific east-bound traffic composition, namely, 8% HDVs and 92% LDVs at rush hour and 15% HDVs and 85% LDVs at midday, based on PTR counts in October, 2007. (Classification data for the same period in 2008 were unavailable.) Traffic volumes used measurements for the segment corresponding to the same periods.

3.4. Comparative analyses between CMEM and MOBILE6.2

Emission estimates were calculated for LDVs and HDVs using CMEM and MOBILE6.2 assuming a constant average speed. For MOBILE6.2, annual average emission factors were estimated using the average vehicle speed, the average of summer and winter emission factors, local estimates of vehicle age distributions, fuel sulfur and oxygenate contents (SEMCOG, 2006), and two vehicle categories (light-duty gasoline vehicle, LDGV; and heavy-duty diesel vehicle, HDDV). CMEM's vehicle categories, which differ from those in MOBILE6.2, use 26 categories for LDVs, broken down by vehicle technology, model year and mileage, weight and fuel

(Scora and Barth, 2006). Total LDV emissions were estimated using eight of these categories and the weights in Table 1, which were based on local vehicle age distribution (SEMCOG, 2006) and the Tier 1 and Tier 2 phase-in implementation schedules (1994–1997 for Tier 1 and 2004–2009 for Tier 2) (EPA, 2000a, 2000b). CMEM did not include HDVs produced after the 2002 model year, and thus we chose the 1998–2002 HDV category, thus both older and newer trucks were not considered. These LDV and HDV categories were assumed to be roughly equivalent to the LDGV and HDDV categories used in MOBILE6.2.

The acceleration noise, defined as the standard deviation of acceleration/deceleration, is a composite indicator of traffic congestion (Smit, 2006). Acceleration noise was calculated for the field study and compared to that derived for the LDV driving patterns in MOBILE6.2 (Smit et al., 2008).

The tabulated results, including statistics for speed, acceleration, deceleration and emission rates, represent trip-based averages and the standard errors among trips. Kolmogorov–Smirnov and Shapiro–Wilk tests were used to examine whether trip-based speed and other results have normal distributions. Kruskal–Wallis and Wilcoxon tests were used to investigate differences in trip-based speeds, accelerations, emission estimates and acceleration noise. Analyses used R 2.7.2 (RFSC, 2008) and Matlab 7.8.

4. Results and discussion

4.1. Speed and acceleration measurements in congestion and free-flow conditions

Table 2 summarizes the collected speed and acceleration data, showing the mean and standard deviation of each parameter among trips for eight traffic conditions. (Additional statistics are shown in Supplemental Table 1.) Based on Kolmogorov–Smirnov (KS) and Shapiro–Wilk (SW) tests, most speed, acceleration, deceleration and emission parameters had normal distributions; for the several parameters that failed these tests, QQ-plots showed that distributions were near to normal. As expected, vehicles were driven faster and more smoothly under free-flow conditions than under work zone and rush hour conditions, and trucks were driven more slowly and more smoothly than cars. Acceleration, deceleration and acceleration noise generally increased as traffic changed from free-flow to transitional and then to congested conditions. Trip-based speeds and accelerations differed by traffic conditions ($p < 0.01$) and vehicle class (LDV vs. HDV) for most conditions, e.g., free-flow conditions ($p < 0.01$).

The lane closure significantly altered traffic patterns. Work zone speeds were low and acceleration noise was high relative to other periods. (Supplemental Fig. 1 shows joint distributions of speed and acceleration/deceleration, stratified by time of a day, vehicle category and traffic conditions.)

Table 1
Weights of CMEM vehicle categories for comparison with the MOBILE6.2 categories.

MOBILE6.2 Category	CMEM Category	Weight
LDGV	Ultra low emitting vehicle (ULEV)	0.13
	Super ultra low emitting vehicle (SULEV)	0.13
	Tier 1 <50k, low power/weight ratio[a]	0.10
	Tier 1 <50k, high power/weight ratio	0.10
	Tier 1 >50k, low power/weight ratio	0.12
	Tier 1 >50k, high power/weight ratio	0.12
	3-way catalyst, fuel injected, >50k miles with low power/weight ratio	0.15
	3-way catalyst, fuel injected, >50k miles with high power/weight ratio	0.15

[a] The cut-off point between high and low power/weight ratio is 0.039 hp lb^{-1} (Scora and Barth, 2006).

4.2. CMEM response surface

Response surfaces for CO emissions and fuel consumption rates for LDVs and HDVs are shown in Fig. 2; response surfaces for other pollutants are shown in Supplemental Fig. 2; and three dimensional plots for each pollutant and fuel consumption are shown in Supplemental Figs. 3 and 4. These figures show emission rates on a g s^{-1} basis, rather than the more common g mi^{-1} basis, to more clearly display effects from short term acceleration and deceleration events. Although the mechanisms that generate emissions of each pollutant differ (as noted in the introduction), the CO response surface in Fig. 2 is fairly typical of the other pollutants. Under acceleration, emission rates increase with vehicle speed, and there is a sharp boundary or "jump" where rates rapidly increase. The boundary is more compressed at high speeds for LDVs, a result of engine characteristics, fuel content and catalytic converter performance. With deceleration, emission rates are low and insensitive to speed, reflecting an unloaded and essentially idling engine.

The response surfaces represent smoothed outputs because CMEM's parameters were calibrated using regression or optimization across multiple vehicles and vehicle classes (Scora and Barth, 2006). The pattern for an actual vehicle would depend on many factors, e.g., vehicle type, year, condition and maintenance, fuel type, etc. Additionally, the jiggles on the contour lines in Fig. 2 are artifacts from discretization and/or contour smoothing. To an extent, the displayed patterns also are sensitive to the choice of contour lines, and some results, especially for HDVs at high speed and high acceleration, may represent extrapolations to infeasible regions.

4.3. Emission estimates for congestion and free-flow conditions

Table 2 lists emission rates (in g mi^{-1}) for the two vehicle classes and four traffic conditions. For LDVs, emissions increased under transition and rush hour congestion periods by 23% for CO, but from only 1–7% for the other pollutants, as compared to free-flow conditions. However, these differences were not statistically significant ($p > 0.05$), suggesting that the variation of trip-based emissions (or fuel consumption) within each condition was large relative to the difference between conditions. Compared to free-flow conditions, work zone congestion showed lower emission rates for HC, CO and NO_x (by 48, 68 and 37%, respectively), but higher CO_2 emission and fuel consumption rates (by 18 and 12%, respectively), changes that were statistically significant ($p < 0.01$). The same trends are seen when expressing emissions as grams of emissions per gram fuel (g g^{-1}) consumed, except for NO_x emitted by HDVs, which have the lowest emission rates within work zones (Supplemental Table 2 shows emission rates in g g^{-1}). These trends can be explained by vehicle speed, acceleration/deceleration, traffic density, and travel time. Acceleration can greatly increase emissions of some pollutants, especially at high speeds when the engine and emission control systems are highly loaded, however, since acceleration periods tend to be brief, impacts on fuel consumption rates over the segment may not be large. As noted earlier, decelerating vehicles have emission and fuel consumption rates that are largely independent of speed. The slower speeds in work zones considerably increase travel time and fuel consumption, for which CO_2 serves as an indicator, but emissions of other pollutants are well controlled in modern engines under such light loads.

For HDVs, the four traffic conditions resulted in emission and fuel consumption rates that were statistically different, except for NO_x between transitional and free-flow conditions. Rush hour and work zone congestion conditions gave the highest HC and CO

Table 2
Summary of speed/acceleration profiles, emission factors and fuel consumption rates for LDV and HDV grouped by traffic condition.

Category	Traffic conditions	No. of Trips	Speed (mph)	Acceleration (mph s^{-1})	Deceleration (mph s^{-1})	Acceleration noise[b] (mph s^{-1})	Emission factors: HC (g mi^{-1})	CO (g mi^{-1})	NO_x (g mi^{-1})	CO_2 (g mi^{-1})	Fuel consumption (g mi^{-1})
LDV	Free-flow conditions	51	70 ± 2[a]	0.22 ± 0.02	−0.20 ± 0.02	0.55 ± 0.12	0.13 ± 0.03	6.59 ± 3.26	0.33 ± 0.05	287 ± 17	97 ± 7
	Transitional period	10	63 ± 1	0.32 ± 0.06	−0.20 ± 0.07	0.75 ± 0.21	0.14 ± 0.03	8.10 ± 3.84	0.35 ± 0.07	289 ± 22	99 ± 7
	Rush hour congestion	10	56 ± 2	0.39 ± 0.04	−0.23 ± 0.55	0.82 ± 0.14	0.13 ± 0.03	6.87 ± 1.87	0.34 ± 0.04	293 ± 17	101 ± 10
	Work zone	11	21 ± 2	0.32 ± 0.05	−0.25 ± 0.05	0.82 ± 0.20	0.07 ± 0.01	2.12 ± 0.74	0.21 ± 0.01	339 ± 19	108 ± 6
HDV	Free-flow conditions	41	63 ± 2	0.17 ± 0.04	−0.16 ± 0.03	0.45 ± 0.09	0.10 ± 0.00	3.58 ± 0.27	16.12 ± 0.94	1660 ± 156	519 ± 49
	Transitional period	7	58 ± 1	0.24 ± 0.04	−0.15 ± 0.04	0.54 ± 0.08	0.11 ± 0.00	4.06 ± 0.22	17.59 ± 1.01	1907 ± 124	596 ± 39
	Rush hour congestion	6	48 ± 5	0.31 ± 0.03	−0.17 ± 0.05	0.64 ± 0.12	0.13 ± 0.01	4.63 ± 0.21	17.93 ± 1.07	2133 ± 92	667 ± 29
	Work zone	11	21 ± 2	0.32 ± 0.06	−0.25 ± 0.07	0.82 ± 0.20	0.26 ± 0.02	6.81 ± 0.54	20.61 ± 1.80	2735 ± 258	852 ± 80

[a] Standard error reflects variations between runs.
[b] Acceleration noise is defined as the standard deviation of acceleration/deceleration.

emission rates; transitional and free-flow conditions gave similar rates. Emission and fuel consumption rates under rush hour congestion increased by 11–31% as compared to free-flow conditions. HC and CO emission and fuel consumption rates jumped sharply with increasing traffic and decreasing speed, strikingly different from the LDV pattern. The highest emission and fuel consumption rates were associated with work zone congestion emissions, which increased HC, CO, NO_x and CO_2 emissions by 158, 90, 28 and 65%, respectively, compared to free-flow conditions.

Our predictions for HDVs are largely consistent with the literature, including results provided by Sjodin et al. (1998) and De Vlieger et al. (2000).However, the lower emissions found for LDVs at low speeds differ from several reports (e.g., Sjodin et al., 1998; De Vlieger et al., 2000; DoTRS, 2001; and Frey et al., 2001). For example, Sjodin et al. (1998) described emission factors for CO, HC and NO_x for the 19–25 mph speed range that were 200%, 200% and 40% higher, respectively, than at 44 mph (the highest speed evaluated). These differences might occur for several reasons. First, results from tunnel or on-board measurements can differ systematically from the data used in CMEM. Older studies using field experiments may be disproportionately affected by vehicles using non-reformulated gasoline, and by older and high emitting vehicles. In contrast, our modeling included both newer vehicles (e.g., ultra low emitting vehicles) and older vehicles (e.g., 3-way catalyst vehicles). Second, emission factors in these studies were either fleet-based (e.g., Sjodin et al., 1998) or individual vehicle-based (De Vlieger et al., 2000; DoTRS, 2001; and Frey et al., 2001).Fleet-based rates in tunnel studies (e.g., Sjodin et al., 1998) might differ from real world due to erroneous dilution assumptions (Jones and Harrison, 2006). However, the on-board studies used relatively few vehicles and might not represent typical conditions. Third, vehicle mix, driving patterns and road type differ among these

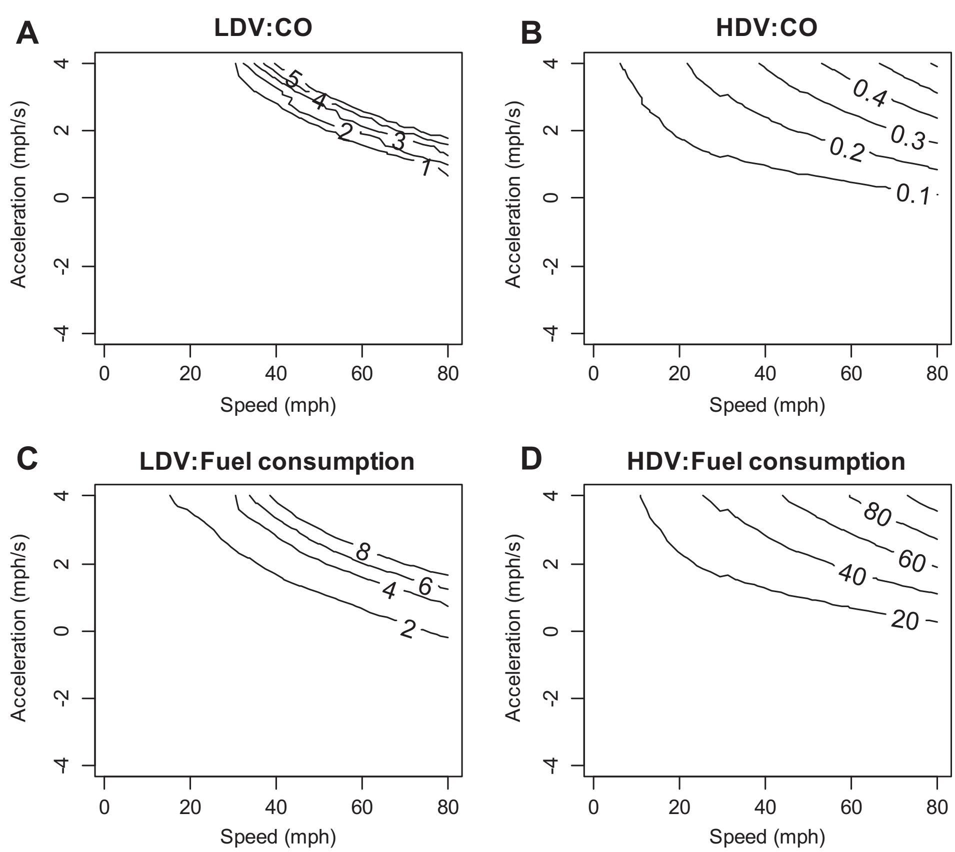

Fig. 2. Response surface for CO emission rates (g s^{-1}) and fuel consumption rates (g s^{-1}) for LDVs and HDVs.

studies, e.g., the case study reflects relatively young vehicles. Differences in road features and regional driving habits may also contribute to observed differences.

Often, a small region in the response surface – typically when both speed and acceleration are high – accounts for disproportionate fraction of pollutant emissions and fuel consumption. For example, the region defined by speeds between 71 and 75 mph and accelerations between 0.4 and 1.5 mph s^{-1} accounted for 13% of the time in the free-flow condition during midday, but 20%, 33%, 28%, 19% and 19% of HC, CO, NO_x, CO_2 emissions and fuel consumption, respectively. Supplemental Fig. 5 shows the emissions contributed by each speed/acceleration (or deceleration) combination.

As an alternative to the second-by-second CMEM simulation, emissions were estimated as the product of the CMEM response surface and the speed/acceleration probability field. For CO, CO_2 and fuel consumption, these estimates closely matched the CMEM simulations (differences below 1%). However, errors for HC and NO_x predictions were large, 10% and 29%, respectively. This results as CMEM predictions depend not only on the current state (e.g., speed and acceleration), but also on previous states (e.g., conditions a few seconds earlier). As examples, CMEM predictions with acceleration and gear shifting show discontinuities ("jumps" and "drops"; Rakha et al., 2003), and catalyst pass fractions are time-dependent (Scora and Barth, 2006). To efficiently and accurately predict HC and NO_x emissions, a more sophisticated approach than response surface modeling is needed to incorporate such "memory" effects.

4.4. Comparison of emission rates for LDV categories

Table 3 shows emission and fuel consumption rate estimates for eight LDV categories and four traffic conditions. In general, results including trends and non-parametric tests followed those seen for (aggregated) LDVs (Table 2), e.g., the lowest emission rates of HC, CO and NO_x and the highest fuel consumption and CO_2 emission rates occurred in work zone conditions. Each LDV category shows similar trends and, unsurprisingly, the newest vehicles (ULEVs and super ultra low emission vehicle or SULEVs) were associated with the lowest emission and fuel consumption rates, followed by Tier 1 and the 3-way catalyst category.

4.5. Comparison of instantaneous- and average-speed predictions

Emission factor predictions for the instantaneous-speed CMEM simulations (derived using the observed speed/acceleration profiles as discussed earlier) are compared to average-speed CMEM predictions in Table 4. For LDVs, average-speed emissions decrease at lower speeds, and emission rates are much lower than instantaneous-speed predictions. The average-speed emission rates do not account for road-specific driving behaviors. For HDVs, the two sets of emission factors showed less variation, and the HC and CO emission rates for instantaneous- and average-speed CMEM simulations were quite similar, although the NO_x emission rates for the instantaneous-speed simulations considerably exceeded (by 59–67%) the average-speed predictions. These results suggest that driving behaviors, as represented by the speed/acceleration profiles, can greatly affect emission rates, especially for LDVs.

The emission factors from MOBILE6.2 systematically differed from CMEM predictions for free-flow conditions. For example, MOBILE6.2 results for LDVs were 2–5 times higher than the instantaneous-speed CMEM estimates and 5–9 times higher than the average-speed CMEM estimates, depending on the pollutant. For HDVs, MOBILE6.2 emissions for HC were higher by 3-fold

Table 3
Summary of emission factor and fuel consumption rates for LDV categories grouped by traffic condition (unit: g mi^{-1}).

Category	Traffic conditions	Emission factors				Fuel consumption
		HC	CO	NO_x	CO_2	
ULEV	Free flow conditions	0.015 ± 0.005	1.7 ± 1.5	0.36 ± 0.06	283 ± 14	90 ± 5
	Transitional period	0.019 ± 0.006	2.8 ± 2.0	0.38 ± 0.08	290 ± 20	93 ± 7
	Rush hour congestion	0.018 ± 0.005	2.0 ± 1.3	0.37 ± 0.05	296 ± 18	94 ± 6
	Work zone	0.014 ± 0.002	0.4 ± 0.4	0.14 ± 0.02	307 ± 18	97 ± 6
SULEV	Free flow conditions	0.017 ± 0.003	1.1 ± 1.1	0.28 ± 0.07	286 ± 14	91 ± 5
	Transitional period	0.020 ± 0.004	1.9 ± 1.6	0.31 ± 0.10	291 ± 19	93 ± 7
	Rush hour congestion	0.019 ± 0.003	1.2 ± 1.0	0.27 ± 0.05	295 ± 18	94 ± 6
	Work zone	0.017 ± 0.001	0.2 ± 0.3	0.09 ± 0.02	303 ± 17	95 ± 5
Tier1 < 50 k, low ratio[a]	Free flow conditions	0.075 ± 0.025	6.6 ± 3.7	0.23 ± 0.03	280 ± 10	92 ± 4
	Transitional period	0.084 ± 0.029	7.9 ± 4.1	0.23 ± 0.03	282 ± 13	93 ± 6
	Rush hour congestion	0.078 ± 0.016	7.1 ± 2.3	0.23 ± 0.02	290 ± 14	95 ± 5
	Work zone	0.036 ± 0.006	1.8 ± 0.9	0.13 ± 0.01	336 ± 19	107 ± 6
Tier1 < 50 k, high ratio	Free flow conditions	0.065 ± 0.037	6.5 ± 4.4	0.15 ± 0.03	311 ± 12	101 ± 5
	Transitional period	0.084 ± 0.045	8.6 ± 5.4	0.17 ± 0.04	315 ± 15	104 ± 7
	Rush hour congestion	0.069 ± 0.021	6.9 ± 2.4	0.16 ± 0.02	323 ± 17	105 ± 6
	Work zone	0.020 ± 0.008	1.5 ± 1.0	0.13 ± 0.01	374 ± 22	119 ± 7
Tier1 > 50 k, low ratio	Free flow conditions	0.097 ± 0.036	7.8 ± 4.3	0.13 ± 0.04	282 ± 10	93 ± 4
	Transitional period	0.112 ± 0.042	9.7 ± 4.9	0.15 ± 0.04	286 ± 13	95 ± 6
	Rush hour congestion	0.102 ± 0.023	8.6 ± 2.7	0.15 ± 0.03	296 ± 15	98 ± 6
	Work zone	0.041 ± 0.009	2.2 ± 1.2	0.11 ± 0.02	342 ± 21	109 ± 6
Tier1 > 50 k, high ratio	Free flow conditions	0.070 ± 0.025	4.3 ± 3.0	0.29 ± 0.03	273 ± 10	88 ± 4
	Transitional period	0.083 ± 0.032	6.1 ± 3.7	0.29 ± 0.03	276 ± 15	90 ± 6
	Rush hour congestion	0.069 ± 0.019	4.3 ± 2.2	0.30 ± 0.03	284 ± 16	92 ± 6
	Work zone	0.030 ± 0.005	0.9 ± 0.5	0.21 ± 0.01	324 ± 18	103 ± 6
3-way catalyst with low ratio	Free flow conditions	0.292 ± 0.038	10.6 ± 4.0	0.64 ± 0.07	289 ± 9	97 ± 4
	Transitional period	0.271 ± 0.087	11.6 ± 5.3	0.63 ± 0.14	288 ± 13	97 ± 7
	Rush hour congestion	0.280 ± 0.031	11.1 ± 2.6	0.67 ± 0.06	299 ± 15	100 ± 6
	Work zone	0.160 ± 0.010	4.3 ± 1.0	0.45 ± 0.03	348 ± 20	112 ± 6
3-way catalyst with high ratio	Free flow conditions	0.310 ± 0.060	13.0 ± 4.8	0.45 ± 0.06	308 ± 10	104 ± 5
	Transitional period	0.327 ± 0.074	14.6 ± 5.2	0.47 ± 0.07	311 ± 14	106 ± 7
	Rush hour congestion	0.307 ± 0.039	13.4 ± 2.7	0.47 ± 0.04	320 ± 15	108 ± 6
	Work zone	0.174 ± 0.011	4.7 ± 1.1	0.32 ± 0.02	376 ± 22	121 ± 7

[a] Ratio refers to power/weight ratio, and the cut-off point between high and low power/weight ratio is 0.039 hp/lb.

Table 4
Vehicle emission factors derived from CMEM using instantaneous-speed profiles and average speeds for LDVs and HDVs by traffic condition (unit: g mi^{-1}).

Category	Traffic conditions	HC emission factors		CO emission factors		NO_x emission factors	
		CMEM-instantaneous speed	CMEM-average speed	CMEM-instantaneous speed	CMEM-average speed	CMEM-instantaneous speed	CMEM-average speed
LDV	Free-flow conditions	0.13 ± 0.03[a]	0.08	6.59 ± 3.26	1.84	0.33 ± 0.05	0.15
	Transitional period	0.14 ± 0.03	0.06	8.10 ± 3.84	1.40	0.35 ± 0.07	0.10
	Rush hour congestion	0.13 ± 0.03	0.04	6.87 ± 1.87	1.03	0.34 ± 0.04	0.07
	Work zone	0.07 ± 0.01	0.03	2.12 ± 0.74	0.56	0.21 ± 0.01	0.02
HDV	Free-flow conditions	0.10 ± 0.00	0.10	3.58 ± 0.27	3.54	16.12 ± 0.94	11.11
	Transitional period	0.11 ± 0.00	0.10	4.06 ± 0.22	3.41	17.59 ± 1.01	10.66
	Rush hour congestion	0.13 ± 0.01	0.12	4.63 ± 0.21	3.46	17.93 ± 1.07	10.75
	Work zone	0.26 ± 0.02	0.25	6.81 ± 0.54	5.13	20.61 ± 1.80	12.94

[a] Standard error reflects variations between runs.

compared to the two CMEM estimates, CO was lower by 51% than two CMEM estimates, and NO_x was 15% lower than the instantaneous-speed CMEM estimates and 23% higher than the average-speed CMEM estimates. Many factors can explain these large differences. First, as shown below, CMEM simulations are sensitive to smoothing of the speed and acceleration data, and differences between CMEM and MOBILE6.2 predictions were significantly diminished when 1 s smoothing was used (3 s smoothing was used in Tables 2–5), which would help to explain the lower CO emissions from HDVs predicted by CMEM. Second, CMEM and MOBILE6.2 treat the vehicle fleet differently. The models used different vehicle category schemes, e.g., CMEM uses 8 car categories but only 1 truck category, and the vehicle-mapping weights (Table 1) could bias results. Since we do not have an independent dataset containing emission rates measured from many vehicles, misclassification error cannot be quantified, and the uncertainties are unknown. Also, MOBILE6.2 uses the local vehicle age distribution, and includes vehicles up to 25 years old. We note that MOBILE6.2 is widely used for regulatory purposes, and is a preferred model for estimating average speed emissions since key auxiliary information, e.g., vehicle age and category distributions, has been established nationally and in many cases regionally. Third, the models use different approaches to estimate emissions, including different driving cycles and different calibration databases. In particular, CMEM used a relatively small number of California vehicles that may not be nationally representative (Scora and Barth, 2006). Finally, MOBILE6.2 does not explicitly account for local-specific speed/acceleration profiles, but rather implicitly handles such profiles in the form of standardized and hopefully representative speed/acceleration profiles. Overall, these models differ in many aspects, and this comparison suggests that uncertainties are high.

4.6. Sensitivity to smoothing and averaging time

Fig. 3 shows the effect of smoothing the speed/acceleration data on CMEM emission estimates for LDVs and HDVs, free-flow and work zone conditions, and the four pollutants. Generally, emission factors decreased as averaging time increased, and changes for LDVs were particularly large, reflecting the sharp boundary shown in the emission response surface (Supplemental Fig. 2). The largest changes occurred at short (1–10 s) averaging times. At longer averaging times, extreme acceleration and deceleration events are "averaged out," and at very long times, emission rates will ultimately converge to that predicted using the average speed. The CMEM results shown earlier used a 3 s averaging time, which might be a reasonable compromise between minimizing potential GPS errors and underestimating real emissions rates. However, the use of 1 or 2 s averaging would significantly increase CMEM predictions, though they still fall below MOBILE6.2's estimates. Clearly, smoothing is a critical factor for instantaneous emission models such as CMEM and MOVES. Probably the best approach to evaluate the required level of smoothing would compare model predictions to simultaneous measurements of vehicle emissions and speed/acceleration profiles. Such model evaluations are clearly needed to ensure the accuracy of predictions from instantaneous emission models like CMEM.

4.7. Acceleration noise comparison

Fig. 4 contrasts acceleration noise in the case study runs with those in the driving patterns used in MOBILE6.2's development. At low speeds, the noise in MOBILE6.2 exceeded that in the case study, reflecting a different congestion pattern. In the case study, the low speed runs were due to work zone congestion, specifically, traffic narrowing from two to one lanes in the east-bound direction. Overall, traffic flow was relatively smooth and not representative of most low speed congestion patterns on freeways. At high speeds, MOBILE6.2's noise was similar to that in the case study. Our results demonstrate considerable variability in the acceleration noise, e.g., for speeds above 60 mph, the noise ranged from 0.35 to 1.13 mph s^{-1}, compared to 0.68 (mph s^{-1}) used in MOBILE6.2. The noise under the four traffic conditions differed statistically ($p < 0.01$).

4.8. Emission intensity and air quality impacts

Emission density estimates (g mi^{-1} s^{-1}) for the case study freeway segment under the three traffic conditions are shown in Table 5. For rush hour congestion, emission densities for HC, CO and CO_2 exceeded those in free-flow periods by 45–95%; the NO_x emission density was slightly higher (7%). For work zone conditions, emission densities decreased from free-flow conditions, particularly for HC and CO; CO_2 increased as discussed earlier.

Table 5
Estimated emission density and fuel consumption density for traffic on the I-94 segment.

Traffic conditions	Emission density				Fuel consumption density (g mi^{-1} s^{-1})
	HC (g mi^{-1} s^{-1})	CO (g mi^{-1} s^{-1})	NO_x (g mi^{-1} s^{-1})	CO_2 (g mi^{-1} s^{-1})	
Free-flow conditions	0.08 ± 0.02	3.67 ± 1.68	1.61 ± 0.11	295 ± 23	96 ± 8
Rush hours	0.13 ± 0.03	7.17 ± 2.62	1.72 ± 0.13	426 ± 26	141 ± 10
Work zone	0.05 ± 0.01	1.54 ± 0.39	1.78 ± 0.15	380 ± 30	120 ± 9

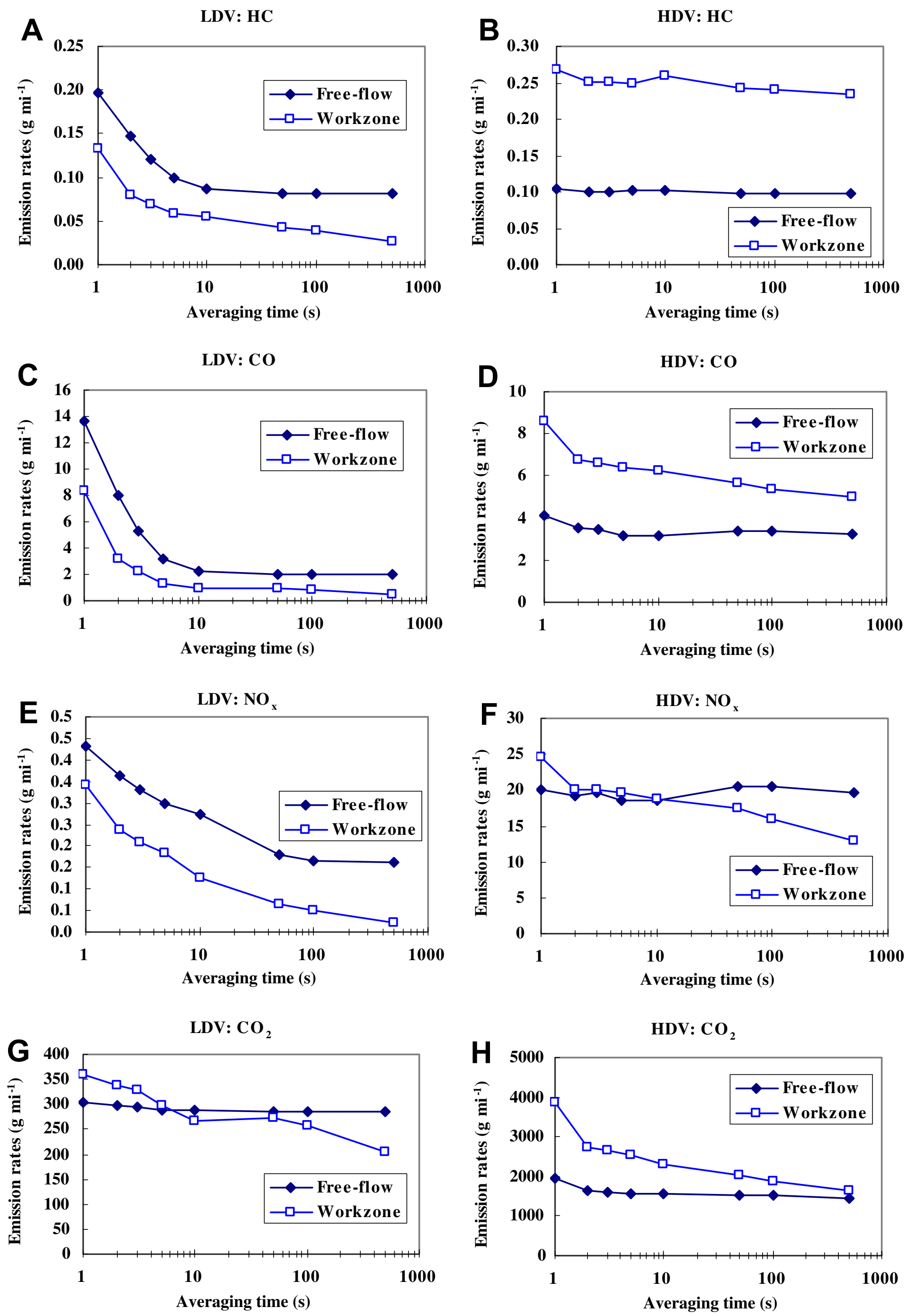

Fig. 3. Sensitivity analysis for smoothing (averaging time) of speed/acceleration data, showing emission rates for LDVs with two speed ranges (20–25 and 70–75 mph, both at midday) and for HDVs using similar speed ranges (20–25 and 60–65 mph, again at midday).

All three conditions differed statistically from one another ($p < 0.01$). These changes result from multiple factors: vehicle volume and travel time, which determines the "packing" or spacing between vehicles; changes in vehicle emission factors; and changes in the vehicle mix. For the study segment, our analysis suggests that rush hour emissions – and concentrations if other factors are constant – of CO and HC will increase near and on the road, while NO_x levels will be similar. These effects are mostly due to higher traffic volumes during rush hour, which increased by 66% compared to free-flow, and a smaller fraction of HDVs during rush hour, which account for 83% of the NO_x emissions. Elevated concentrations of HC and CO, and other pollutants not modeled by CMEM, e.g., $PM_{2.5}$, would increase exposures of commuters, who also endure longer travel times during congestion. It would also increase exposures of individuals living or working near major roads.

4.9. Evaluation of the approach

Emission estimates are typically derived using macroscopic emission models, e.g., MOBILE6.2, in combination with static traffic models, such as TransCAD (a transportation planning software), to

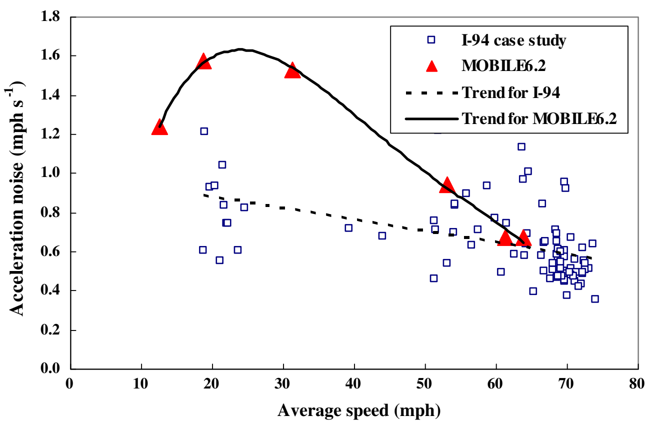

Fig. 4. Comparison of acceleration noise on using measurements for the I-94 field study and MOBILE6.2 LDV driving patterns.

predict regional emissions for conformity analyses and other air quality planning purposes. Models used in such applications may inaccurately represent emissions for specific road links and times, and performance may be poor when simulating congestion since emissions may deviate considerably from free-flow conditions. Such circumstances have motivated efforts to combine micro-simulation traffic models, e.g., VISSIM, with instantaneous emission models, e.g., CMEM, along with air quality dispersion models (Cappiello, 2002; Chevallier, 2005; Boulter and McCrae, 2007). By modeling the movements of individual vehicles on a second-by-second basis, or even shorter intervals, micro-simulation models simulate many of the complex driver behaviors that are observed in real networks. Because driving behavior varies with location, time of day, and day of week, such simulations require data and calibrations for vehicle speed and acceleration/deceleration distributions, as well as parameters related to car-following, lane-changing, and driver aggressiveness. With appropriate input data, micro-simulation models can simulate the wide range of vehicle behaviors found on roads. Although the full integration of micro-simulation traffic and instantaneous emission models is computationally intensive, the current high power computers allow applications for both small and large road networks (Lee et al., 2009; Stevanovic et al., 2009).

The integration of speed–acceleration probabilities and response surface analyses for instantaneous emission models like CMEM, when appropriately calculated (e.g., using small bins), represents a simple and fast way to derive CO and CO_2 emission factors tailored to local driving behavior, including the stop-and-go transients encountered in congestion. However, enhancements are needed to account for memory effects that affect HC and NO_x emissions. The speed–acceleration data obtained using the car-floating or potentially other technique obviate the need to calibrate and run computationally and parameter-intensive micro-simulation models. The approach is highly amenable to sensitivity and other analyses. However, emission rates might be underestimated because the measured speed profiles tend to represent the fleet average, e.g., aggressive driving behavior might be underrepresented.

4.10. Study limitations

This study has several limitations. First, due to model limitations, we did not estimate emissions of particle matter, ultrafine particles, and black carbon that are emitted primarily by HDVs and that are associated with health risks (WHO, 2005). Second, as mentioned, speed/acceleration profiles developed using the car-floating technique generally represent an average profile among vehicles on the road, and because we followed a limited number of vehicles, may not necessarily represent the full range of conditions. This would tend to underestimate actual emissions. Third, the mapping between CMEM and MOBILE6.2 categories was based on the southeast Michigan vehicle age distribution, not the actual distribution on the study segment. Fourth, the vehicle categories in CMEM were calibrated using mainly vehicles before the year 2000. As a result, we could not consider gas-electric hybrid and biofuel-based vehicles. Fifth, we did not consider the newer emission standards for diesel trucks, including standards for 2004 and 2007 year and later vehicles (EPA, 2002), thus CMEM emissions may be overestimated. Biases may be smaller for LDVs because the SULEV category used is roughly equivalent to the current EPA Tier 2 emission standards. Additionally, the MOVES model (EPA, 2009) is appropriate for this work, as recently demonstrated by Gouge et al. (2010) which used a similar approach to model emissions using this model and instantaneous-speed profiles. (A comparison of MOVES and CMEM is planned for a follow-up study.) Both models may inadequately represent "gross emitters" that can account for a disproportionate share of emissions. Sixth, we did not use site-specific monitoring to validate the modeling and the model inter-comparison. Seventh, while we demonstrated that smoothing of the field study data affected results, we had no independent test to evaluate the appropriate degree of smoothing. Eighth, in a comparison of three emission models, Rakha et al. (2003) indicated that CMEM showed some abnormal behavior for LDVs under certain conditions, e.g., CO emission estimates abruptly dropped under low speed and high acceleration levels, possibly due to the complexity of modeling engine operations. Finally, we examined a single freeway link. Clearly, additional applications are needed to generalize findings.

5. Conclusions

This study examined pollutant emission and fuel consumption rates under free-flow, work zone and rush hour congestion conditions using a microscopic approach. In the freeway study and for LDVs, the transitional period when traffic is either slowing down from free-flow to congestion conditions, or accelerating from congestion to free-flow conditions, was associated with slightly higher emission rates of CO, HC and NO_x compared to free-flow and rush hour conditions; low speed work zone congestion had much lower emission rates. The pattern for HDVs was very different: Work zone congestion was associated with the highest emissions of CO, HC, NO_x and CO_2.

Considering the combined effect of driving behavior, vehicle volume and mix, and emission factors, on- and near-road concentrations of CO, HC and NO_x are expected to nearly double during rush hour periods as compared to free-flow periods, given similar dispersion conditions. Clearly, link-specific emission rates depend on the degree and type of congestion. While only a few congestion conditions were analyzed, the results highlight the importance of congestion for emission, exposure and health risk evaluations, as well as conformity analysis in transportation planning.

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Appendix. Supplementary material

Supplementary data related to this article can be found online at doi:10.1016/j.atmosenv.2011.01.030.

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