ABSTRACT

LIU, BIN. Quantification and Evaluation of Onroad Light Duty Vehicle Tailpipe Emissions. (Under the direction of Dr. H. Christopher Frey).

Emissions from onroad vehicles are a major source of air pollution in the United States. Vehicle emission factors can be quantified by model estimates and empirical measurements. Model estimates need to be evaluated based on empirical data for its accuracy and sensitivity on emissions. To get accurate emissions from model estimates, vehicle activity is an important input and needs to be quantified as the performance envelope of acceleration and speed. Because of the large sample size of the empirical data and MOVES computational intensity, and simplified version of MOVES is needed to evaluate the sensitivity of factors that affect emissions, and to couple with traffic simulation model.

The MOter Vehicle Emission Simulator (MOVES) is an onroad mobile source emission model developed by the U.S. Environmental Protection Agency (EPA). EPA has evaluated MOVES based on limited data not used in model development. To evaluation MOVES sensitivity with independent empirical data, emission were measured in-filed for 100 light duty vehicles son multiple routes using a Portable Emissions Measurement System (PEMS). For each vehicle, modal fuel use and emission rates are estimated based on ranges of Vehicle Specific Power (VSP). The VSP modes are weighted by time spent in each mode for multiple real-world driving cycles that represent different mixes of arterial and highway driving for cycle averages speeds from 20 to 65 mph to represent cycle average emissions rates. Empirical onroad emission measurements of 100 vehicle also recorded vehicle type, age, driving cycles, and ambient conditions, which are input to MOVES estimations. Comparing empirical emission factors and MOVES estimates, MOVES estimates of cycle

average CO_2 emission rates are sensitive to vehicle type, cycle average speed, and road types, but not model year or age, and the trends are consistent with empirical data. MOVES emission rates for NO_x, CO, and HC are sensitive to vehicle type, model year, age, and cycle average speed, as are the empirical data.

As one of the input to emission models for estimating emission factors, accurate estimation of vehicle activity is critically important to accurate estimation of emissions. To provide a benchmark for estimation of vehicle speed trajectories, such as from traffic simulation models, a method for quantifying the vehicle performance envelope based on real world activity data for 100 light duty vehicles is developed. The vehicle performance envelope is quantified in terms of the 95 percent frequency range of acceleration for each of 15 speed bins with intervals of 5 mph, and a speed bin for greater than 75 mph. Potential factors affecting the performance envelope are evaluated, including vehicle type, transmission type, road grade, engine displacement, engine horsepower, curb weight, and ratio of horsepower to curb weight. The performance envelope is wider speeds ranging from 5 mph to 20 mph, and narrows as speed increases. The latter is consistent with a constraint on maximum achievable engine power demand. The envelope is weakly sensitive to factors such as type of vehicle, type of transmission, road grade, and engine horsepower. The effect of road grade on cycle average emission rates is evaluated for selected real-word cycles. An approach for evaluating standard dynamometer driving cycles, such as the FTP, HFET, SCO3, and US06 cycles, in comparison to the empirically-derived performance envelope, is demonstrated. A key finding is that the effect of inter-vehicle variability on the performance envelope was minor, implying that the envelope can be quantified based on a smaller vehicle sample than used here.

MOVES can be used to couple with travel demand models (TDMs) and traffic simulation models (TSMs) for the purpose of estimating emissions impacts of possible future changes in road infrastructure, vehicle mix, traffic control measures, and other factors. However, MOVES is computationally intensive, and direct dynamic coupling of MOVES to a TDM or TSM can be impractical. To facilitate the capability to estimate link-based emission factors based on second-by-second vehicle speed trajectories, a simplified version of MOVES is demonstrated here. A Cycle correction factor (CCF) is generated for a selected vehicle type and driving cycle based on distribution of time spent in each of 23 operating mode bins. Operating modes are defined by the instantaneous speed and Vehicle Specific Power (VSP). The emission factors estimated by the simplified model are demonstrated to be sensitive to differences between driving cycles with similar average speeds. The errors of the simplified model cycle average predictions are within ±1% for 92% of the cases among pollutants, ages, and driving cycles, for passenger cars, passenger trucks, light commercial trucks, single unit short haul trucks, and combination long haul trucks. The application of the simplified model is demonstrated based on empirical driving cycles observed from field measurements.

After the simplified version of MOVES has been updated to taking account corrections of ambient conditions including temperature and humidity, variability in light duty vehicles emissions based on vehicle type, age, driving cycles, and ambient conditions is assessed using the simplified version of MOVES as a high throughput tool (HTT). To evaluate the separate and interactive impact of the sources of variability, case studies with combinations of two vehicle types (passenger car and passenger trucks), two model year (vehicles subject to Tier 1 and Tier 2 emission standards), and three ambient conditions (low, medium and high temperature) are compared based on 591 empirical driving cycles of each case.

Empirical driving cycles including second by second speed, acceleration, and road grade were measured in RTP, NC area for 100 light duty vehicles on both freeways and non-freeways. A multivariate rank regression based method (SRRC) is used in the analysis for case study based on empirical vehicle type, age, driving cycles, and ambient conditions for the interactions of factors. Based on the results, emission factors are most sensitive to temperature, cycle average speed, and standard deviation of speed.

The overall contributions of the research is to provide a large sample size of empirical emission data and vehicle activity data to evaluate model estimates, and to develop a simplified emission model that can runs much faster for evaluation the sources of variability such as vehicle type, age, model year, driving cycles, and ambient conditions.

Quantification and Evaluation of Onroad Light Duty Vehicle Tailpipe Emissions

by
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DEDICATION

This dissertation is dedicated to my family.

BIOGRAPHY

Bin Liu was born in city of Shenyang, China. She received her bachelor degree in environmental sciences from Beijing Forestry University in 2008, from where she started to research in air pollution and air quality field. She got her master degree in hydraulic and environmental engineering from University of Macau in 2010, with her thesis of urban heat island effect in Macau. She joined Department of Civil, Construction, and Environmental Engineering in 2010 under supervision of Dr. H. Christopher Frey. Her research focuses on measurement and modelling of light duty vehicle tailpipe emissions.

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Finally, but the most important, I would like to thank my parents and my husband Dongbo Zhao. Their love gives me the strength during my study.

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PART I **INTRODUCTION**

INTRODUCTION

Emission from onroad vehicles is one of the major source of air pollution in United States (U.S.EPA, 2013). Quantification and evaluation of emission factors and inventories are the critical foundation for air pollution control and air quality management.

There are several method of quantifying onroad vehicle emission factors including empirical measurements and model estimation. Driving cycle models estimate emissions based on cycle average speed and other variables such as vehicle fleet, vehicle age, fuel consumption and climate such as MOBILE6 (U.S. EPA, 2003). Modal models, such as Moter Vehicle Emission Simulator (MOVES) and the Comprehensive Modal Emissions Model (CMEM), estimate vehicle emissions based on estimates of engine load that depend on high resolution data regarding the vehicle speed trajectory (Chamberlin, 2011; Stevanovic and et al, 2009; Kite, 2011)

MOVES is the current model used by U.S. EPA and has been evaluated with limited independent data. There is a need of evaluating MOVES sensitivity of emissions on some factors such as vehicle characteristics (vehicle type, age, model year) and vehicle activities (driving cycles, cycle average speed) and road type (freeways and non-freeways). Therefore, empirical measurements of emissions and vehicle activity is needed for MOVES sensitivity evaluation.

Empirical measurements include dynamometer lab test, remote sensing method, and onroad measurements. Dynamometer test is conducted in laboratories with standard driving cycles and cannot represent the real world driving conditions (Chiang, et al, 2008). Remote sensing

method is location specific and cannot get emission data for a driving cycles or link (Kuhns, et al, 2004). Onroad measurement has a good representation of real world conditions and can measure the emissions for driving cycles or origin/destination pairs.

Study design of the empirical measurements covers a wide range of vehicle age, model year for light duty vehicles and a wide range of driving cycles. Cycle average emission factors of empirical data is calculated based on modal average emission rates and fraction of time spent in modal modes. Vehicle Specific Power (VSP), calculated based on speed, acceleration, and road grade is used as the basis for modal modes (Jime ́nez-Palacios, 1999).

Vehicle acceleration and speed are important emissions model inputs. Vehicle acceleration and speed can be estimated by traffic simulation models (TSMs), which estimate speed trajectories for individual vehicles based on car-following and lane-changing theories (Alexiadis, et al, 2004). However, there are few published evaluations of TSM trajectory predictions. Real-world data regarding reasonable upper bounds on acceleration as a function of speed are needed to calibrate and bound TSM simulated trajectories. Therefore, quantification of the acceleration versus speed performance envelope is needed.

Travel demand models (TDMs) and TSMs can provide more spatial coverage of estimated vehicle activity, and can be used to evaluate what-if strategies regarding future transportation improvement projects (TIPs) or traffic control measures (TCMs). Since MOVES is a computationally intensive model, there is a challenge to couple MOVES with TSMs. A simplified version of MOVES is needed to couple with TSMs easily and to run faster.

The simplified version of MOVES enable the rapid evaluation of sensitivity analysis for variability. The model with corrections of ambient conditions can be used for estimating emission factors of multiple driving cycles under any ambient conditions.

LITERATURE REVIEW

Literature reviews have been conducted for the main parts of the dissertation.

TABLE I-1 Literature Review in Dissertations

Content	**Location**
Models for estimating emission factors	Part II, Part IV
MOVES algorithm	Part II
Vehicle specific power	Part II, Part III, Part IV, Part V
EPA evaluation of MOVES	Part II
Study design of empirical measurements	Part II, Part III, Part V
Sources of variability in emission factors	Part II, Part V
Challenge and opportunity in coupling emission models and traffic simulation model	Part IV
Factors affecting speed and acceleration performance envelope	Part III
EPA standard driving cycles	Part III

OBJECTIVES

The objectives of the study are :

(1) to evaluate the sensitivity of MOVES emission rates to selected key factors, including vehicle types, cycle average speed, road type, model year, age and mileage, and to compare with sensitivity of independent empirical data for the same factors;

(2) to quantify the typical performance envelope of acceleration versus speed for light duty vehicles in real world vehicle activity and the factors and evaluate the factors affect the performance envelope and evaluate standard driving cycles representation of real world vehicle activity with respect to the typical speed-acceleration performance envelope;

(3) to develop a simplified reduced form version of MOVES provide accurate estimates of relative changes in cycle average emission rates for a range of pollutants and vehicle types and evaluate the sensitivity of cycle average emission rates to variations in driving cycles based on factors such as average speed and road type;

(4) to evaluate the variability of vehicle types, age, driving cycles and ambient conditions on emissions using a high throughput tools.

ORGANIZATION

This dissertation is consist of six parts. Part I is introductions, objectives, and the organization of the studies. Part II is comparing MOVES estimates and empirical emission factors. Part III is evaluating the performance envelope of light duty vehicles speed and acceleration. Part IV is developing a simplified version of MOVES that is accurate and runs

3,000 times faster than MOVES. Part V is evaluating the source of variability in Part VI is summary of the findings, conclusions, limitations, and recommendation for future studies.

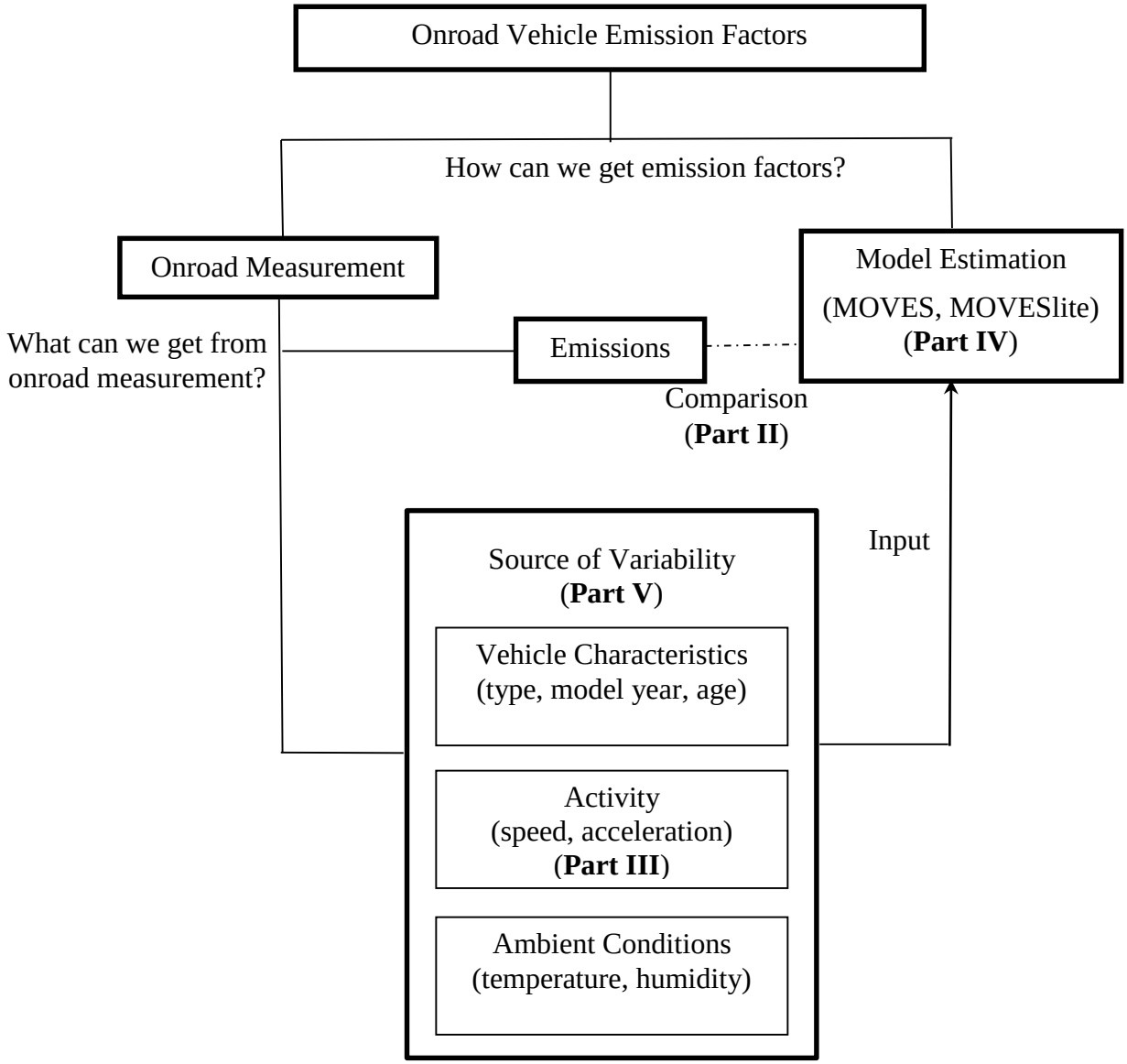


Figure I-1 Overview Scope of the Research

Figure I-1 Continued

Arrows mean input to model.

Dashed line means comparison between measured emissions and simulated emissions.

PART II COMPARISON OF DRIVING SCHEDULE PROJECT LEVEL MOVES EMISSION FACTORS TO EMPIRICAL DATA

ABSTRACT

The MOter Vehicle Emission Simulator (MOVES) is an onroad mobile source emission model developed by the U.S. Environmental Protection Agency (EPA). MOVES is used widely in the U.S. to estimate onroad vehicle emission rates. EPA has evaluated MOVES based on limited data not used in model development. Here, the sensitivity of MOVES emission factor estimates to selected light duty vehicle types, model years, real-world driving cycles, and road type is evaluated based on independent tailpipe emission data. These data were measured on multiple routes for 100 vehicles including passenger cars, passenger trucks, and hybrid electric vehicles using a Portable Emissions Measurement System (PEMS). For each vehicle, modal fuel use and emission rates are estimated based on ranges of Vehicle Specific Power (VSP). The VSP modes are weighted by time spent in each mode for real-world driving cycles that represent different mixes of arterial and highway driving for cycle averages speeds from 20 to 65 mph. MOVES estimates of cycle average CO2 emission rates are sensitive to vehicle type, cycle average speed, and road types, but not model year or age, and the trends are consistent with empirical data. MOVES emission rates for NOx, CO, and HC are sensitive to vehicle type, model year, age, and cycle average speed, as are the empirical data. The similarity in relative responses between MOVES and the empirical data builds confidence that the findings from either are robust. Both MOVES and data from PEMS can be used with confidence as the basis for relative comparisons used in transportation planning, pollution control and air quality management.

INTRODUCTION

About 30% of carbon dioxide (CO2), 60% of carbon monoxide (CO), 34% of nitrogen oxides (NOx), and 29% of hydrocarbon (HC) U.S. national emissions are from on-road mobile sources.[1] These four pollutants are either key greenhouse gas (GHG) influencing climate change, or linked with adverse effects on human health.[2-5] Accurate vehicle emission factors are necessary to development of effective air quality management strategies.[6]

The MOtor Vehicle Emission Simulator (MOVES) developed by the U.S. Environmental Protection Agency (EPA) is widely used to quantify vehicle emission.[7-10] MOVES has undergone limited evaluation based on comparison of predicted tailpipe running exhaust emission factors for selected vehicle types and pollutants to independent data not used for model development.[11] Given its widespread use, there is a need for further evaluation of MOVES. This paper demonstrates a method for model evaluation based on independent measurements made during real world driving of in-use tailpipe emissions of 100 light duty vehicles. The method is demonstrated with a focus on comparison of how well MOVES predicts observed relative trends in CO2, NOx, CO, and HC emission rates based on selected key factors that affect variability in emissions.

MOVES is a modal emission model that estimates vehicle emissions based on operating modes (OpModes) for Passenger Cars (PCs), Passenger Trucks (PTs) and other vehicle types. OpMode bins are defined based on Vehicle Specific Power (VSP) and speed.[7] Cycle average emission factors are calculated based on the time distribution of OpModes. A user can enter 1 Hz speed, acceleration and road grade, using the project level capability of MOVES, to

estimate cycle average emission factors. OpMode bin emission rates in the MOVES default database are from chassis dynamometer tests.

Dynamometer tests, Remote Sensing Device (RSD) measurements and tunnel study data were used by EPA to evaluate fuel-based emission factors for 1978 to 2008 model year light duty vehicles.11 The MOVES fuel based estimates of NOx, CO, and HC emission factors were within -5% to +5% of empirical data for 2004 and newer vehicles, and within -40% to +200% for older vehicles. However, the reported evaluation of MOVES has several limitations. Although the dynamometer data include a large number of vehicles, only a limited range of driving conditions were considered based on the IM240 and LA92 driving cycles with average speed of 29.4 and 24.6 mph, respectively. RSD measurements are for vehicles driving at approximately 25 mph. Both RSD and tunnel study data are location-specific. The evaluation was made for fuel-based emission factors, which are less sensitive to vehicle engine load than distance-based emission factors. Since MOVES is typically used to estimate emission factors on a gram per mile base, the evaluation should be on the same basis. Therefore, real world data for driving cycles with wide range of cycle average speeds are needed.

Portable Emission Measurement Systems (PEMS) can be used to obtain running exhaust emissions on a second-by-second basis during real world driving. PEMS have been used to measure vehicle emission factors for route average emissions for a variety of vehicle types and routes.[12-15]

The research objective here is to demonstrate a method for evaluating the sensitivity of MOVES emission rates to selected key factors, including vehicle types, cycle average speed, road type, model year, age and mileage, based on comparison to sensitivity of independent PEMS-based empirical data for these same factors. This type of evaluation is critical to building confidence in the suitability of how MOVES estimate respond to these sources of variation and, therefore, regarding the adequacy of MOVES for development of emission inventories and policy planning and evaluation purposes.

METHODOLOGY

MOVES project level emission factor estimates are compared with empirical on-road vehicle emission factors obtained from field measurements using PEMS.

MOVES Emission Factors

MOVES estimates emission factors for a user defined "link" or "cycle" with 1 Hz speed and road grade. MOVES is a fleet model, which means that it cannot estimate emission rates for a specific year, make, and model vehicle. Rather, it estimates a fleet average rate for a given calendar year, age, and vehicle type (U.S. EPA, 2009). To enable comparisons, the key inputs to MOVES are specified to match as closely as possible those of vehicles measured using PEMS including vehicle type, fuel type, age, calendar year, temperature, humidity, and 1 Hz speed and road grade. MOVES output includes cycle average emission factors in grams per mile. CO_2 emission factors are estimated based on fuel consumption reported by MOVES and typical gasoline fuel properties.

Empirical Data

Empirical data were obtained from emission measurements in the Raleigh and Research Triangle Park (RTP) area in NC.[15, 16]

PEMS measurements at 1 Hz were made of tailpipe concentrations of CO_2, CO, HC and NO using the Global MRV Axion system. This PEMS was previously found to have good concordance with dynamometer measurements for CO_2, NO_x, and CO.[17] For HC, the measurements tend to be biased low by a factor of two because the non-dispersive infrared (NDIR) detection method responds well to straight-chain hydrocarbons but has lower response ratios for other hydrocarbons.[18] However, the relative variation in the HC measurements were similar to the relative trend of the dynamometer laboratory measurements.

Vehicle location and elevation were recorded using Global Position System (GPS) receivers with barometric altimeters, from which road grade was estimated.[19] An on-board diagnostic (OBD) link scantool was used to record engine data.[20]

To account for variability in real world vehicle operation, measurements were conducted between two Origin/Destination (O/D) pairs: from NC State University (NCSU) to North Raleigh (NR), and from NR to Research Triangle Park (RTP).[16] Route C is split into a freeway cycle C_F and a non-freeway cycle C_NF. Likewise, Route 1 is split into a freeway cycle 1_F and a non-freeway cycle 1_NF. Therefore, there were typically six cycles measured for each vehicle, including four non-freeway cycles A, 3, C_NF, 1_NF, and two freeway cycles C_F and 1_F. In previous research, this set of study routes was demonstrated

to be adequate for quantifying variability in fuel use and emission rates over a wide range of engine loads.[12, 16]

One hundred vehicles were measured between 2008 and 2013, including 63 PCs, 32 PTs, and five hybrid electric vehicles (HEVs). The measured vehicles include 1996 to 2013 model years that were 0 to 14 years old at the time of the measurement, with 600 to 230,000 accumulated miles per vehicle, engine displacement ranging from 1.3 to 5.4 L, and curb weight ranging from 2,340 lb to 5,820 lb.

Data processing and quality assurance (QA) includes four major steps: (1) converting OBD data to a second-by-second basis; (2) synchronizing data from multiple instruments into one database; (3) range checks and data screening to correct or remove data errors; and (4) modal analysis of the data.[20] The total estimated fuel use was compared with actual gas pump fuel use. Time based emission factors in grams per second were estimated based on 1 Hz estimated fuel use rate and measured pollutant concentration. VSP, an indicator of engine load, is quantified based on speed, acceleration, and road grade with coefficient values for a typical light duty vehicle:[21]

$$\text{VSP} = \quad v\left\{1.1 \times a + 9.81\left(\frac{r}{100}\right) + 0.132\right\} = 0.000302 \times v^3 \qquad (1)$$

Where,

VSP = Vehicle Specific Power , kW/ton

v = Vehicle speed, m/s

a = Vehicle acceleration, m/s^2

r = road grade,%

VSP has been categorized into 14 modes based on detailed statistical analysis.[16,22] Modes 1 and 2 have negative VSP values associated with deceleration or traveling downhill, Mode 3 includes zero VSP which represents idling, and Modes 4 to 14 are for increasing positive VSP values associated with acceleration, hill climbing, or cruising. Average emission rates in grams per second for each vehicle are calculated for each VSP mode. CO_2, NO_x, CO, and HC emission rates in gram per second are typically lowest in VSP mode 3, and increase with increasing positive VSP.[12] Cycle average distance-based emission factors are calculated based on VSP modal emission rates and time spent in each VSP mode:

$$EF_{p,veh,c} = \frac{\sum_{m=1 \text{ to } 14}(ER_{p,veh,m} \times t_{m,c})}{L_c} \quad (2)$$

$EF_{p,veh,c}$ = empirical cycle average emission factor for pollutant p, specific measured vehicle veh, and cycle c, grams per mile

$ER_{p,veh,m}$ = empirical modal emission rates for pollutant p, vehicle veh, for the mth VSP mode, grams per second

$t_{m,c}$ = time spent in the mth VSP mode, cycle c, seconds

L_c = length of the cycle c, miles

p = pollutant, such as CO_2, NO_x, CO, or HC.

Comparison of MOVES and Empirical Emission Factors

The purpose of the comparison is to evaluate whether the trends in cycle average emission factors predicted by MOVES are similar to those observed in the empirical data.

Emission Factors

Emission factors estimated based on MOVES are compared to those inferred from empirical data. In some cases, direct comparisons are made for clearly defined categories. In other cases, comparisons are made taking into account variability in a potential explanatory factor using linear regression.[23, 24] Furthermore, in some cases, analysis of the parity between MOVES and empirical emission factors is done using linear regression. As an example of the latter, approximately 600 cycle average emission factors, based on approximately 6 real-world cycles measured for each of 100 vehicles, used to compare MOVES and empirical data. The statistical hypothesis to be tested is that the empirical emission factors are linearly related to MOVES estimates:

$$\mathrm{EF}_{\mathrm{p,veh,c}} = \mathrm{a_p} \times \mathrm{EF}_{\mathrm{p,vehm,c}} + \mathrm{b_p} \tag{3}$$

$\mathrm{EF}_{\mathrm{p,vehm,c}}$ = MOVES cycle average emission factor for pollutant p for a fleet average value of a vehicle of the same type, model year, fuel and ambient conditions, grams per mile

$\mathrm{a_p}$ = slope for pollutant p, dimensionless

$\mathrm{b_p}$ = Intercept for pollutant p, grams per mile

The statistical significance and goodness of fit of the hypothesized linear relationship are evaluated using the F ratio for the model and the coefficient of determination, R^2, respectively.

Vehicle Type and Model Year

PCs, also known as light duty vehicles (LDVs), have gross vehicle weight rating (GVWR) ≤ 2700 kg. Over 99% of U.S. PCs are gasoline fueled.[25] PTs, including minivans, pick-up trucks, and sport utility vehicles (SUVs), have GVW≤ 3900 kg. Over 98% of U.S. PTs are gasoline fueled. PCs and PTs are subject to the same tailpipe emission standards for NO_x, CO, and HC. However, because of variations in weight, there is inter-vehicle variability in the rate of fuel consumption and CO_2 emissions.[26] The purpose of the comparison here is to identify differences, if any, between PCs and PTs with respect to CO_2, NO_x, CO, and HC emission factors. The hypothesis is that the CO_2 emission factors are higher for PTs than for PCs because of their typically greater weight. However, since PCs and PTs are certified to the same emission standards, the hypothesis is that emission rates of NO_x, CO, and HC are similar. Unpaired two-sample t-tests are used to evaluate the differences in PC and PT emission factors.

Model year is associated with variability in tailpipe emission rates because emission standards change over time.[27] Tier 1 tailpipe standards phased in since 1994 for NO_x, CO and HC are 0.4 g/mi, 3.4 g/mi, and 0.41 g/mi, respectively. Tier 2 standards phased in since 2004 for the most common "bin 5" category are 0.05 g/mi, 3.4 g/mi, and 0.075 g/mi, respectively. Therefore, in-use NO_x and HC emission rates for later model year vehicles are expected to be

lower. The measured 1996 to 2003 model year vehicles were certified to Tier 1 standards, and the 2004 to 2013 model year vehicles were certified to Tier 2 standards. Cycle average emission factors are compared for Tier 1 and Tier 2 vehicle groups for each of PCs and PTs.

Cycle Average Speed

CO_2, NO_x, CO, and HC cycle average gram per mile emission factors are each sensitive to cycle average speed and typically reach a minimum at speeds in the range of 40 to 60 mph.[28, 29] Cycle average emission factors are estimated and compared based on observed real-world cycles with average speeds of 10 mph to 70 mph in increments of 10 mph, and for observed cycles over 70 mph. The speed-based comparisons enable characterization of the trend in cycle average emission factors versus cycle average speed.

Road Type

Emission factors are sensitive to road types because of differences in driving cycles.[30] Vehicles operating on city roads have higher mass per distance rates of fuel consumption and emissions compared to freeways.[31] Pairwise differences between each combination of two cycles among the six observed are estimated for each vehicle, including comparisons between urban arterials and freeways.

Age and Mileage

Age and mileage accumulation are factors associated with deterioration of emission control systems such as the catalytic converter.[32] On a fleet average, NO_x, CO, and HC emissions are typically weakly dependent on mileage accumulation, whereas fuel economy and CO_2

emission rates typically are not.[28, 33] MOVES accounts for deterioration of tailpipe exhaust NO_x, CO, and HC emission rates, assuming that the most rapid change occurs for vehicle ages between 4 and 10 years.[7]

Linear regression is used to test the hypothesis that empirical emission factors are affected by mileage and age, including a multiplicative term for interactions between the two:

$$\mathrm{EF_{p,veh}} = \mathrm{a_{p,0}} + \mathrm{a_{p,1}} \times \mathrm{A_{veh}} + \mathrm{a_{p,2}} \times \mathrm{M_{veh}} + \mathrm{a_{p,3}} \times \mathrm{A_{veh}} \times \mathrm{M_{veh}} \quad (4)$$

$\mathrm{A_{veh}}$ = age of the specific measured vehicle, years

$\mathrm{M_{veh}}$ = mileage of the specific measured vehicle, mile

However, because MOVES does not allow mileage as a user input, only age is considered.

$$\mathrm{EF_{p,vehm}} = \mathrm{a_{p,0}} + \mathrm{a_{p,1}} \times \mathrm{A_{veh}} \quad (5)$$

The analyses were done separately for Tier1 PCs, Tier 2 PCs, Tier 1 PTs, Tier 2 PTs, and HEVs. However, because MOVES does not have a category for HEVs, only empirical data were analyzed for trends related to HEVs.

RESULTS

There are more than four hours of continuous driving among six driving cycles for each measured vehicle. Therefore, there are approximately 1.4×10^6 seconds of 1 Hz driving cycle and emission rate data. For each of 97 vehicles, data are available for six driving cycles. For each of 3 vehicles, data are available for only three driving cycles. Therefore there are a total

of 591 cycle average emission rates estimated for each of CO_2, NO_x, CO, and HC for both empirical data and MOVES estimates.

Empirical Modal Emission Rates

VSP modal average CO_2 and NO_x emission rates are shown in Figure 1 for each of five categories, including: Tier 1 PCs; Tier 2 PCs; Tier 1 PTs; Tier 2 PTs, and HEVs. For CO_2, the lowest emission rates are for VSP mode 3. The average VSP modal rates increase with positive VSP. The highest modal average rate is approximately a factor of 8 to 11 greater than the lowest rates over the five categories. For NO_x, the highest to lowest modal average rates vary by a factor of 26 to 74, indicating substantial variation in average NO_x emission rate with increasing engine load. The modal average rates vary by a factor of 53 to 72 for CO, and by 8 to 11 for HC. Overall, NO_x, and CO have more variability with engine load than CO_2.

For PCs, Tier 2 vehicles have VSP modal average NO_x emission rates that are 23 percent to 64 percent lower than Tier 1 vehicles. Except for VSP Mode 1, the HC modal average rates are 18 percent to 36 percent lower. The CO modal rates are 41 percent to 68 percent lower. The CO_2 emission rates are approximately the same. For PTs, Tier 2 vehicles have modal average emission rates lower than those of Tier 1 by 79 percent to 87 percent for NO_x,10 percent to 34 percent for HC, and 13 percent to 52 percent CO. Thus, the Tier 2 standard is effective at lowering emissions of NO_x, HC, and CO compared to Tier 1.

As a result of their larger weight, PTs typically have 34 percent to 74 percent higher CO_2 modal average emission rates than PCs. They also tend to have higher HC and CO modal

average emission rates. For Tier 1 vehicles, modal average NOx emission rates of PTs tend to be higher than those of PCs, especially for higher values of VSP. However, for Tier 2 vehicles, modal average NO_x emission rates of PTs are 49 percent to 79 percent lower than for PCs. Thus, although vehicle size is clearly a determinant of CO_2 emission rate, it is not a determinant of the emission rates of the regulated tailpipe emission pollutants.

Similar to other reported results,[34] HEVs have substantially lower NO_x, CO, and CO_2 emissions than Tier 2 PCs.

Comparison of MOVES and Empirical Data

Cycle average emission factors in grams per mile are compared between MOVES estimates and empirical data.

All Data

Figure 2a shows empirical emission factors versus MOVES estimated emission factors for CO_2 for 591 cycle average comparisons. The MOVES estimated CO_2 cycle average emission factors range from 267 g/mi to 790 g/mi, which correspond to fuel economy of 33 to 11 miles per gallon (mpg). The empirical CO_2 cycle average emission factors range from 160 g/mi to 832 g/mi. Empirical emission factors lower than 200 g/mi are from HEVs, such as a 2006 Toyota Prius, or low fuel consumption conventional vehicles, such as a 2006 Scion tC. In contrast, MOVES does not have a separate HEV vehicle type. Empirical emission factors higher than 800 g/mi are from larger PTs such as a 2011 Ford F150. The empirical emission factors have a statistically significant linear relationship with MOVES estimates. The slope of the trend line is 1.03 with a standard error of 0.04, which means on average there is no

bias between empirical and MOVES estimates. The scatter in the comparison is attributed primarily to inter-vehicle variability in the empirical data. Overall, the cycle average CO_2 MOVES estimates agree well with the empirical data.

In Figure 2b, the MOVES estimated NO_x emission factors range from 0.025 g/mi to 2.2 g/mi with a mean of 0.38 g/mi. The cluster of values close to the origin of the graph represent HEVs and newer Tier 2 vehicles, including both PCs and PTs. MOVES NO_x emission rates higher than 0.82 g/mi, and empirical NO_x emission rates higher than 0.23 g/mi, are all from Tier 1 vehicles. The fitted trend line is statistically significant but the trend is weak, with R^2 of only 0.36. However, there is substantial inter-vehicle variability in the comparison. A possible key factor associated with generally higher MOVES values is that the default emission rate database for MOVES is reported to take high emitting vehicles into account.[7] Thus, the proportion of high emitters may be higher for MOVES than in the empirically observed data. Qualitatively, the empirical and MOVES estimates covary appropriately with respect to clusters of lower emitting and newer Tier 2 and HEVs, with higher values being associated with Tier 1 vehicles.

For CO, the MOVES estimated cycle average emission rates range from 0.007 g/mi to 11 g/mi with a mean of 3.2 g/mi and the empirical estimates range from 0.005 g/mi to 8.2 g/mi, with a mean of 1.0 g/mi. For HC, the MOVES estimates range from 0.004 g/mi to 0.43 g/mi, with a mean of 0.062 g/mi and the empirical estimates range from 0.0007 g/mi to 0.34 g/mi, with a mean of 0.072 g/mi. Thus, the two sets of estimates are of similar magnitude for both pollutants.

Vehicle Types and Model Year

The mean cycle average emission rates for all measured vehicles and cycles for multiple vehicle groups are shown in Figure 3 for both MOVES and empirical estimates. For both MOVES and empirical CO_2 cycle average emission rates, there is little difference between Tier 1 and Tier 2 for either PCs or PTs, which indicates that these emissions are not sensitive to model year. Fleet average fuel economy standards for 1990 to 2013 model years were 27mpg to 34 mpg for PCs and 20 mpg to 26 mpg for PTs, depending on the model year.[35] PTs have 40 percent to 60 percent higher cycle average CO_2 emission rates than PCs, for either Tier 1 or Tier 2, because PTs are larger vehicles with more weight and engine displacement.

For cycle average NO_x emission rates, the qualitative trends among vehicle groups are similar for PCs and PTs. The Tier 2 PCs have average rates that are about 87 percent lower than Tier 1 for both MOVES and empirical estimates. The Tier 2 PTs have average rates that are 75 percent and 86 percent lower than Tier 1 for MOVES and empirical estimates, respectively. Based on MOVES, PTs are estimated to have higher NO_x emission rates for PTs than for PCs for a given Tier; however, the empirical data indicate that PCs and PTs, which are subject to the same standard, have similar average emission rates. The empirical emission rates are below the level of the emission standards to which the vehicles were certified, whereas the MOVES estimates are higher than such levels. However, the cycles used as the basis for the estimates reported here are not the same as the certification driving cycles. The magnitude of the MOVES average emission rates is higher than that of the

empirical data most likely because MOVES may account for a higher proportion of high emitting vehicles. The cycle average rates for the HEVs are substantially lower, by 63 percent, compared to the Tier 2 PCs.

Tier 2 PCs have cycle average CO emission rates that are 55 percent and 61 percent lower than Tier 1 for MOVES and empirical estimates, respectively. The MOVES and empirical Tier 2 PTs emission rates are 60 percent and 38 percent lower than Tier 1, respectively. Based on empirical data, cycle average rates for HEVs are 76 percent lower than for Tier 2 PCs. The magnitude of the MOVES estimated CO emission rates ranges from 120 percent to 260 percent higher than the empirical estimates among the PC and PT groups, most likely because MOVES accounts for a greater proportion of high emitters. However, the qualitative trend between Tier 2 versus Tier 1 is similar. Similarly, for HC emission rates, both Tier 2 PCs and PTs have 22 percent to 89 percent lower than Tier 1 vehicles for empirical and MOVES data.

Cycle Average Speeds

Trends in cycle average CO_2 and NO_x emission rates with respect to cycle average speed are shown in Figure 4 for both MOVES and empirical estimates. CO_2 cycle average emission rates are typically highest at low cycle average speed, and tend to decrease monotonically to a minimum typically near 60 mph. For example, for Tier 1 PCs, the MOVES cycle average CO_2 emission rate is 480 g/mi at 10 mph to 20 mph, and decreases to 300 g/mi at 60 mph to 70 mph. Likewise, the Tier 1 PC empirical rates are highest at the lowest speed range, and

tend to decrease with increasing speed. There is a small sample size in the 40 mph to 50 mph range that leads to noise in the trend, and the small sample size and high inter-cycle variability at speeds over 70 mph lead to an inclusive finding with regard to very high average speeds. However, overall, the qualitative relative trend is concordant between MOVES and empirical estimates for both Tier 1 and Tier 2. Moreover, the variation in cycle average speed leads to more variation in emission rates, ranging over 200 g/mi, compared to the differences among the Tier 1 and Tier 2 vehicles or between MOVES and the empirical estimates, which range over 100 g/mi or less. Fuel use and CO_2 emission factors can be reduced by 50% if vehicles are driving at optimum speed compared with driving below 20 mph. The speed trend for PTs is similar to that of PCs.

For NO_x emissions, the highest rates occur at both low and high speeds, and the lowest rates typically occur around 40 mph to 50 mph for both MOVES and empirical estimates. Depending on the vehicle group and emissions tier, the NO_x emission rates at moderate speed are 20 to 70 percent lower than at low speed. Although the magnitude of the emission factors differ between the empirical and MOVES estimates, the relative qualitative trends are similar.

For CO and HC, the trends are similar to that for NO_x, with higher emission rates at low and high speed, and lower emission rates at moderate speed. The lowest CO emission rates are 40 percent smaller than the emission rates at low speed for both MOVES and empirical data. The lowest HC emission rates are 67 percent and 50 percent smaller than the emission rates

at low speed for MOVES and empirical data, respectively. Therefore, cycle average speed can significantly affect fuel economy and emissions.

Road Types

Cycle average emission rates for CO_2 and NO_x are compared in Figure 5 among four non-freeway and two freeway cycles based on Tier 1 and Tier 2 PCs. Results are qualitative similar for PTs. The CO_2 emission rates are highest for Routes C_NF and 1_NF, which have the lowest cycle average speeds. The rates are lowest for the two freeway routes. Comparing the two freeway cycles to the two highest emitting non-freeway cycles, the emission rates are about 30 percent lower for both Tier 1 and Tier 2 PCs based on MOVES estimates, and correspondingly 40 percent lower based on empirical estimates. Thus, the qualitative relative trends are similar between the two data sources.

There is high correlation in the emission rates when comparing routes. For example, the correlation in CO_2 emission rates between any pair of the six cycles ranges from 0.82 to 0.95. For the other pollutants, the inter-cycle correlation is 0.95 or greater. Thus, it is highly likely that a vehicle that has high (low) emissions on one cycle also has high (low) emissions on any of the other cycles. Taking into account this correlation, CO_2 emission factors for each of the two freeway cycles are significantly lower than for any of the non-freeway cycles. However, the emission factors are not significantly different when comparing among the four non-freeway cycles or among the two freeway cycles.

For cycle average NO_x emission rates, there are no statistically significant differences when comparing any pair of cycles for a given data series, such as for MOVES estimates for Tier 1

PCs. The lower speed non-freeway cycles have a portion of higher NO_x emission rate operation at low speeds, whereas the freeway cycles have a portion of higher NO_x emission rate operation at high speeds. Thus, even though the speed distributions of the cycles differ, the trend in NO_x emission rates for low and high speeds tend to compensate in this particular comparison.

For CO, there are no significant differences in mean rates for any pairwise comparison of cycles, but over 70 percent of the vehicles are estimated to have higher emission rates for the freeway versus non-freeway cycles for both MOVES and empirical data. For HC, the cycle average emission rates are 35 percent lower for the freeway versus non-freeway cycles, but are not significantly different when comparing only among freeway or among non-freeway cycles.

Age and Mileage

Mileage increases by an average of 10,300 miles per year as age increases, based on empirical data. CO_2 MOVES and empirical emission factors are not statistically significantly affected by age or mileage. MOVES NO_x cycle average emission rates are sensitive to vehicle age; they increase by 0.02 g/mi to 0.09 g/mi per year for five groups. Except for Tier 1 PTs, empirical NO_x cycle average emission rates are significantly related to both age and mileage. MOVES CO and HC cycle average emission rates increase as age increases. Empirical CO cycle average emission rates are significantly correlated to age and mileage for PCs, but not for PTs or HEVs. Empirical HC cycle average emission rates significantly increase as age and mileage increase. Overall, CO_2 is not sensitive to age or mileage but

other pollutants are sensitive to one or both of these factors for most if not all vehicle groups. The trend of increase of emission factors versus age and mileage are consistent for MOVES and empirical data.

DISCUSSION

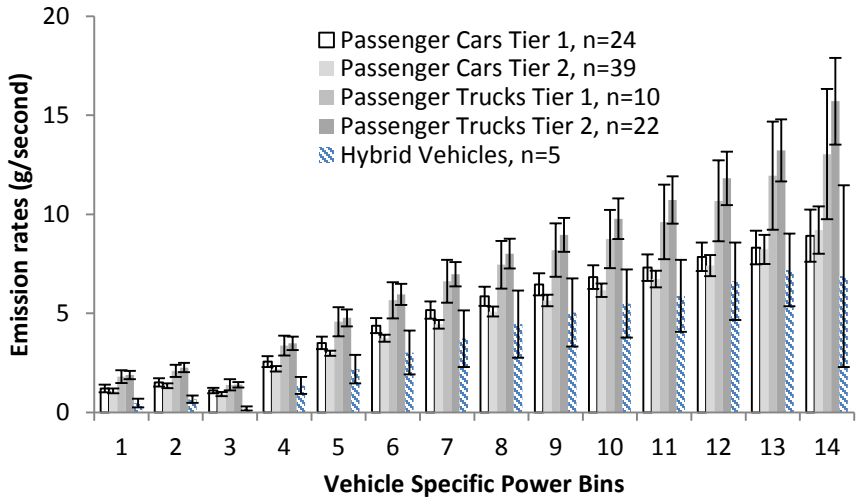
As expected, empirical emission factors and MOVES estimates are sensitive to model year, vehicle type, speed, road type, and age. The main contribution of this paper is to evaluate MOVES sensitivity to a variety of factors with independent empirical data that covers a wide range of speeds for real-world driving cycles. Overall, the trends in MOVES estimated emission factors with respect to driving cycles, vehicle type, regulatory tier, and related factors such as cycle average speed, road type, vehicle age, and mileage accumulation are qualitatively consistent with those observed in independent empirical data. However, since HEV NO_x, CO, and HC emission factors are 30% to70% lower than for a conventional vehicle of the same emission standards, there is a need to add HEV as a vehicle type in MOVES.

This is the first time that MOVES has been evaluated for a wide range of real-world driving cycles based on independent field measurements of emissions. Based on the concordance in relative trends for both MOVES and the empirical data, both information sources can be used in what-if scenarios for transportation planning, pollution control and air quality management.

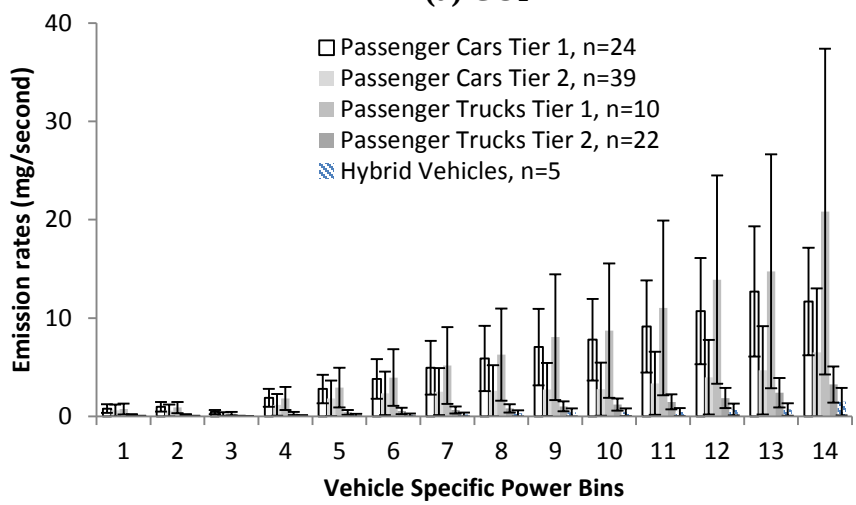
A method for developing and comparing independent empirical data to predictions of MOVES is demonstrated here; however, the methodological approach can be improved and

extended in several important ways. The vehicle sample for the independent empirical data does not adequately represent high emitters. Thus, a strategy and resources for recruiting and measuring high emitters is needed, such as using remote sensing to identify potential high emitters, and offering owners of such vehicles compensation to participate in PEMS data collection. Some important emissions processes were not addressed here, such as the effect of cold starts on trip emissions. We are addressing cold starts in a separate research effort. The set of vehicles to be considered can be expanded to medium duty gasoline trucks (e.g., large pickup trucks), and various medium and heavy duty diesel vehicles, for a more comprehensive evaluation of MOVES. The development of empirical data could be extended to additional pollutants, such as speciated hydrocarbons, using additional portable measurement instruments. Measurements could be conducted under a wider range of climatic and topographical conditions to observe more variability in ambient conditions and road grade. The effect of vehicle age on deterioration rate of emission controls requires a large sample of data to obtain statistically significant trends and, thus, remains an ongoing need for model evaluation.

Nonetheless, despite the limitations of the current work, this research demonstrates that comparisons can be made between independent empirical data and MOVES to provide insight regarding factors that affect variability in vehicle emission rates. Although consistency in trends between the empirical data and MOVES is not a guarantee that either are "correct," the similarities in trends is a confidence building measure that implies that insights regarding key sources of variability are robust.

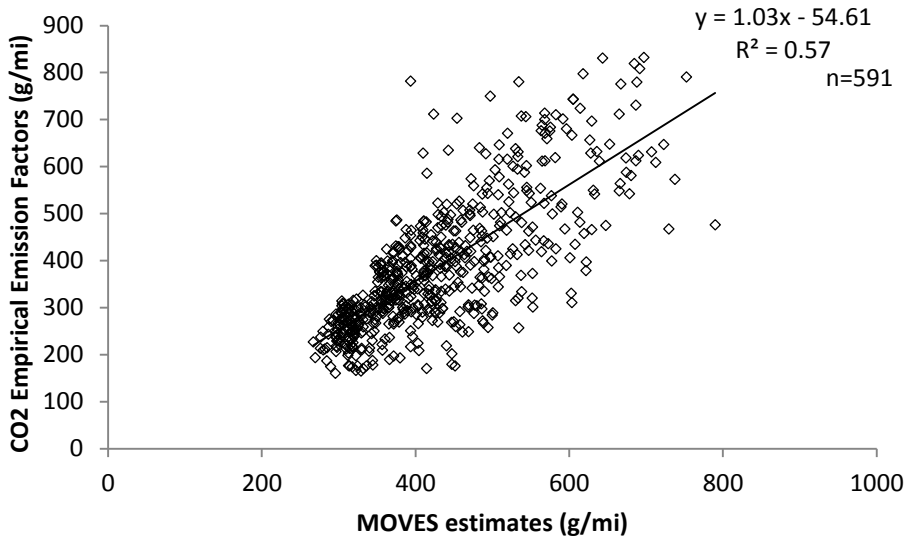


(a) CO_2

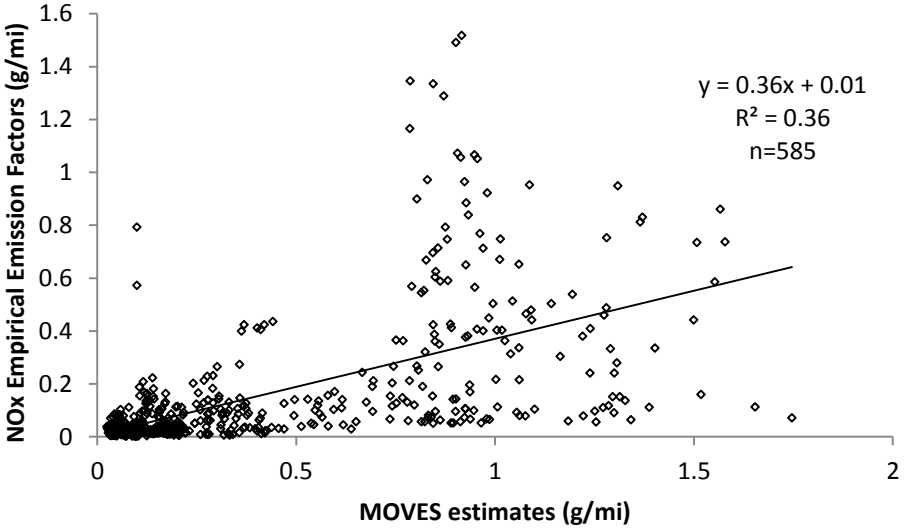


(b) NO_x

Figure II-1 Average CO_2 and NO_x VSP Modal Emission Rates and 95% Confidence Intervals for Tier 1 and Tier 2 Passenger Cars and Passenger Trucks, and Hybrid Electric Vehicles

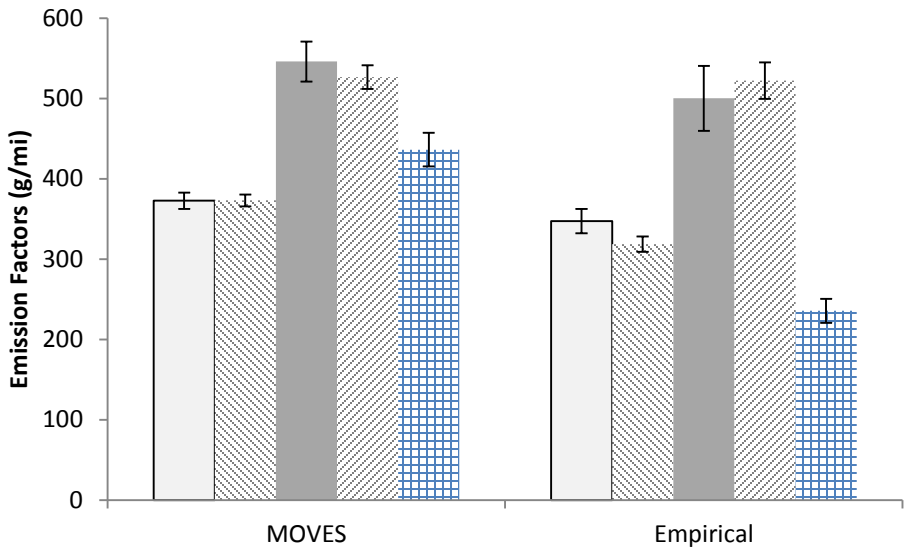


(a) CO_2

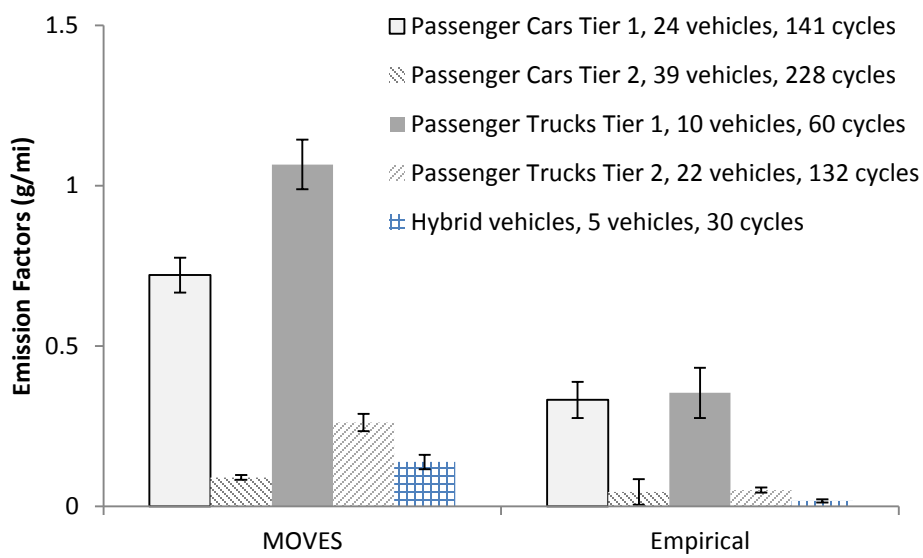


(b) NO_x

Figure II-2 Empirical CO_2 and NO_x Emission Factors vs MOVES Estimates for 591 Observed Driving Cycles for 100 Vehicles for CO_2 and 585 cycles for 99 vehicles for NO_x

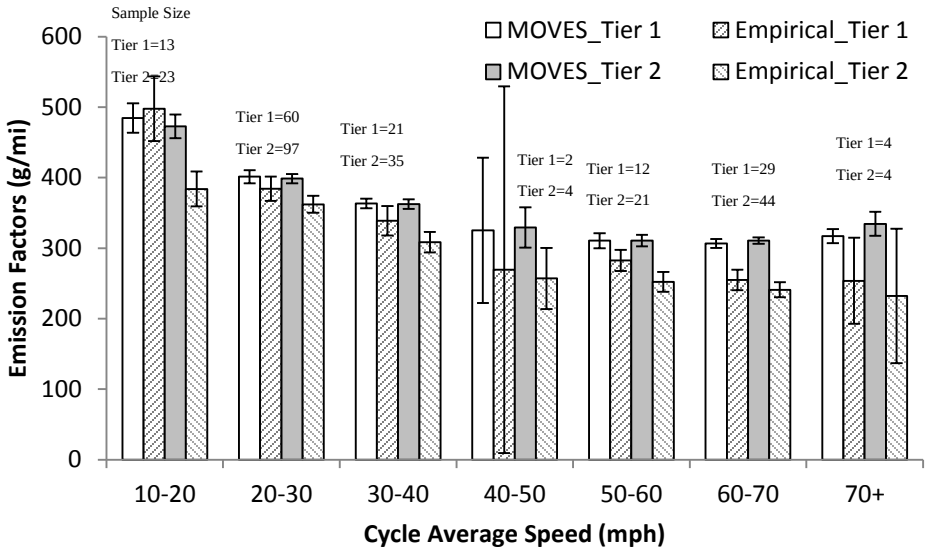


(a) CO_2

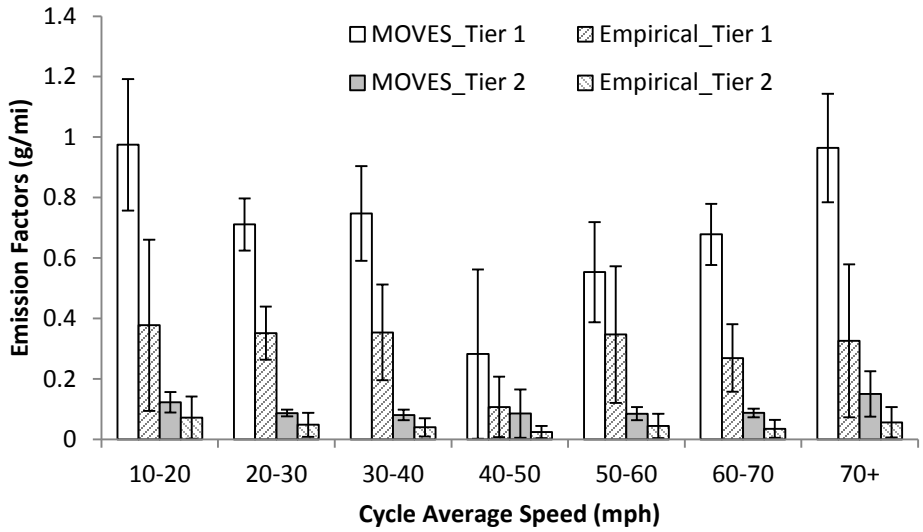


(b) NO_x

Figure II-3 Cycle Average CO_2 and NO_x Emission Factors and 95% Confidence Intervals of Tier 1 and Tier 2 Passenger Cars and Passenger Trucks and Hybrid Electric Vehicles for MOVES Estimates and Empirical Data. The MOVES estimates for comparison to HEVs are a weighted combination of Tier 2 PCs and PTs.

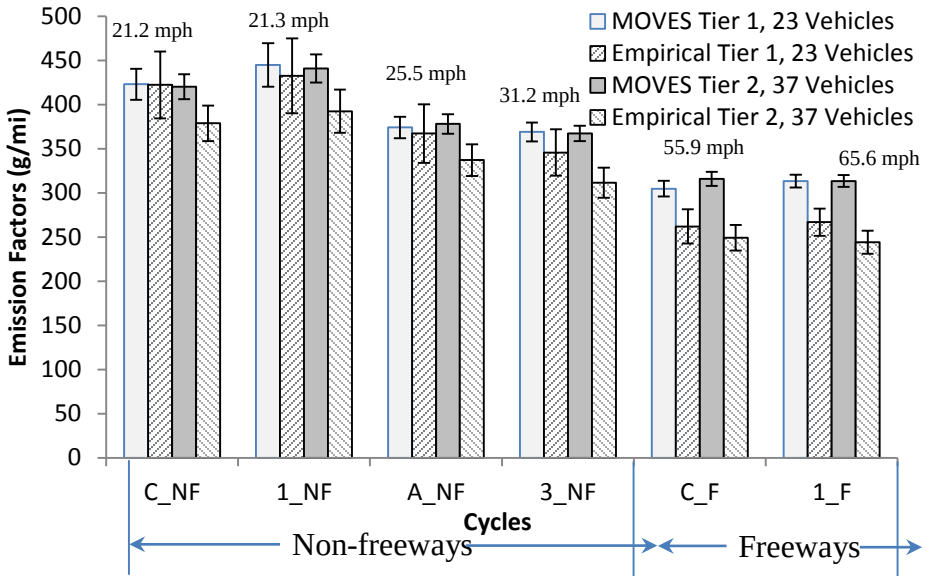


(a) Passenger Cars CO_2

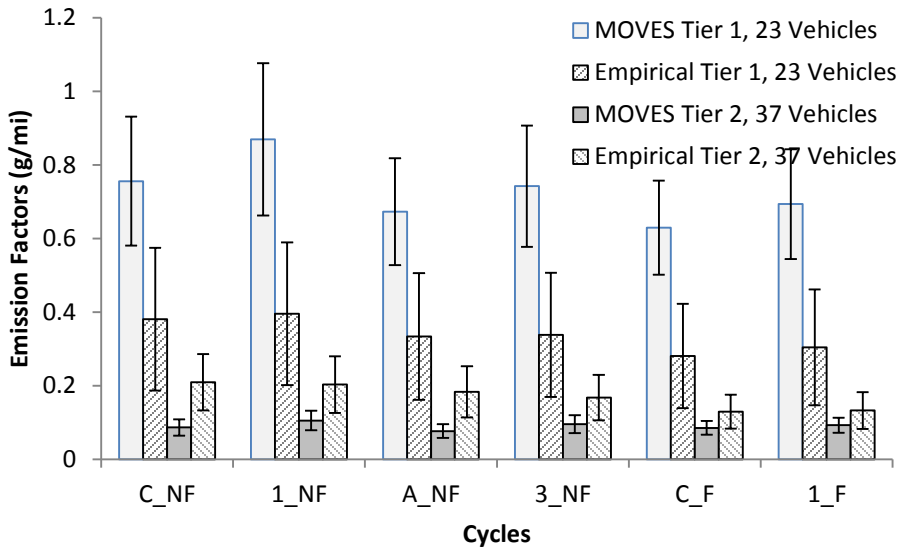


(b) Passenger Cars NO_x

Figure II-4 Cycle Average CO_2 and NO_x Emission Factors and 95% Confidence Intervals Based On MOVES Estimates and Empirical Data For Tier 1and Tier 2 Passenger Cars For Selected Ranges of Cycle Average Speed



(a) Passenger Car CO_2



(b) Passenger Car NO_x

Figure II-5 Cycle Average CO_2 and NO_x Emission Factors and 95% Confidence Interval for Selected Cycles for MOVES and Empirical Data For Tier 1 and Tier 2 Passenger Cars

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Some of the data used in this paper have been collected and used in previous research. Additional data collections are conducted to bring total number of vehicles to 100.

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PART III **MEASUREMENT AND EVALUATION OF REAL-WORLD LIGHT DUTY VEHICLE SPEED AND ACCELERATION ACTIVITY ENVELOPE**

ABSTRACT

Light duty gasoline vehicles (LDGVs) , including passenger cars (PCs) and passenger trucks (PTs) comprise more than 70% of the U.S. onroad vehicle fleet. LDGV exhaust emission rates vary with vehicle type, age, driving cycle, and ambient conditions. Although these factors have been evaluated individually, they have not typically been evaluated simultaneously in a consistent framework that also accounts for their interactions. These factors and their interactions are evaluated based on nearly 600 real-world driving cycles measured for 100 LDGVs. These data include PC and PT vehicle types, 1996 to 2013 model years, a variety of road types, and a range of ambient temperature and relative humidity. To deal with the combinatorial challenges of parametric evaluation of these factors, and to enable evaluation of multiple sources of variability simultaneously using a consistent framework, a High Throughput Tool (HTT) was developed, which is a simplified version of the U.S. EPA's MOVES model that runs 1,000 times faster. The HTT is verified and shown to be accurate and precise compared to MOVES predictions. The variability in emission factors between PC and PT, between model year groups that represent different regulatory certification standards, among the real-world cycles, and among a range of ambient conditions are individually and jointly evaluated. CO_2 and NO_x cycle average emission factors are sensitive to vehicle type, ambient conditions, and driving cycles. NO_x emission factors are also sensitive to model year and emission standards. Reductions in NO_x emissions for newer versus older vehicles are larger for passenger cars than passenger trucks. Differences in CO_2 and NO_x emission rates due to temperature are more pronounced for driving cycles with low cycle average speeds. The unique contribution of this work is that

the comparisons are based on a large sample of real-world driving cycles and thus are representative of real world conditions.

INTRODUCTION

Real world tailpipe emissions are related to engine load, which can be quantified as Vehicle Specific Power (VSP), calculated based on speed, acceleration, and road grade (1, 2, 3). Under conditions of low to moderate road grade, VSP is typically most sensitive to speed and acceleration. Furthermore, some vehicle emissions models are based on speed and acceleration matrixes (4). Therefore, vehicle acceleration and speed are important emissions model inputs (4, 5, 6).

Vehicle speed and acceleration can be estimated by traffic simulation models (TSMs), which estimate speed trajectories for individual vehicles based on car-following and lane-changing theories (7). However, there are few published evaluations of TSM trajectory predictions. In one evaluation, the speed trajectories predicted by a TSM were found to be in error, leading to errors of 30 to 80 percent in estimates of emissions for nitrogen oxides (NO_x), carbon monoxide (CO), and hydrocarbons (HC) (8). Real-world data regarding reasonable upper bounds on acceleration as a function of speed are needed to calibrate and bound TSM simulated trajectories (9). TSMs are often used to make predictions of the activity of light duty vehicles including passenger cars (PCs) and passenger trucks (PTs), which comprise more than 80 percent of the U.S. onroad fleet (10, 11). Therefore, this paper focuses on quantification of the acceleration versus speed performance envelope for such vehicles.

Factors Affecting Acceleration and Speed

There are several factors related to vehicle characteristics that may affect vehicle performance capability in terms of high end acceleration versus speed. Akcelike and Besley

take vehicle type, such as light and heavy vehicles, into account when estimating instantaneous speed and acceleration in a TSM (12). Light trucks have slower acceleration than cars because of larger aerodynamics losses due to higher drag coefficients and larger frontal area (13). Vehicle acceleration is reported to be weakly related to engine displacement, and to be proportional to horse power (14, 15). The maximum achievable acceleration is inversely proportional to vehicle weight; in particular, heavy vehicles are reported to have only 30% capability for acceleration at highway speeds versus low speed (16, 17). Manual transmissions may deliver slightly larger accelerations than automatic transmissions (13).

Road Grade

Road grade can be taken into account using "effective acceleration," taking into account force exerted from gravity (18). Road grade affects fuel use and emissions (19, 20, 21). For example, emission rates of CO_2, NO_x, CO, and HC can be underestimated by 14 to 42 % if the positive road grade of 5% or more is ignored (22).

EPA Standard Cycles

There are two main regulatory programs that involve measurement of either the fuel use or emission rates of light duty vehicles using chassis dynamometers based on standardized driving cycles, including fuel economy rating and certification of emission standards (23, 24). The Federal Test Procedure (FTP) is based on a commuting trip in Los Angeles in the 1970s (25, 26). The Highway Fuel Economy Test (HWFET) is based on free-flow highway traffic conditions (27). For both of these cycles, the maximum acceleration was limited to

not more than 3.3 mph/s to avoid problems of vehicle tire slippage on dynamometer rollers, and thus neither of these cycles challenges vehicle performance (28). As a result, the FTP and HWFET have been criticized as not being representative of real-world activity with smaller range of acceleration (26, 29). To achieve more realistic fuel economy estimates, the US06 and SC03 cycles were added to the fuel economy rating procedure (26). The US06 is typically considered to be an aggressive cycle that features high rates of acceleration over a range of speeds, including freeway speeds (28). SC03 was designed as a supplement to the FTP (30). Given their widespread use, results developed in this paper are compared to the FTP, HWFET, US06, and SC03 driving cycles.

Needs For Additional Work

A systematic methodological approach is needed for quantifying the real-world performance envelope of vehicle acceleration versus speed for the purpose of calibrating TSMs. Data on the real-world performance envelope of high end acceleration rates versus speed are also useful for judging the adequacy of a standard driving cycle for representing real world activity, and thus can be used to evaluate such cycles. Furthermore, prior knowledge of typical achievable performance envelops can inform study design for in-use measurement of vehicle activity, energy use, and emissions with Portable Emissions Measurement Systems (PEMS) and assessment of whether a particular measurement achieved sufficient variability in operating conditions to be generalizable (31, 32).

Research Questions

The key research questions addressed here are: (1) what is the typical performance envelope of acceleration versus speed for light duty vehicles in real world vehicle activity?; (2) what factors affect the performance envelope?; (3) does road grade play an important role in effective acceleration?; and (4) do standard driving cycles represent real world vehicle activity with respect to the typical speed-acceleration performance envelope?

METHODS

Methods of this study include study design for obtaining real-world data on vehicle performance envelopes, instruments used for data collection, and analysis and interpretation of the measured data.

Study Design

Study design accounts for choice of vehicles, study routes, time of day, fuel, and drivers (33). Since 2008, field measurements have been conducted on 100 light duty vehicles, including 63 passenger cars (PCs), 32 passenger trucks (PTs) and 5 hybrid electric vehicles (HEVs). The vehicles were selected to cover a wide range of model years, age, accumulated mileage, engine size, and vehicle weight.

To account for variability in real world vehicle activity, measurements were conducted on two alternative routes between each of two Origin/Destination (O/D) pairs from NCSU to North Raleigh (NR) and from NR to Research Triangle Park (RTP) (33). The routes include a mix of road functional types including feeder/collector streets, minor arterials, major

arterials, freeways, and ramps. The set of study routes was demonstrated to be adequate for quantifying variability in fuel use and emission rates over a wide range of engine load (33, 34).

Instrumentation

An on-board diagnostic (OBD) link scan tool was used to record vehicle engine data, including Vehicle Speed (VSS) (33). Acceleration is estimate based on the difference in speed of the current and previous second. Vehicle location and elevation were recorded using Global Positioning System (GPS) receivers with Barometric Altimeter (BA), from which road grade was estimated (22).

Vehicle Characteristics

In Table 1, the sample size, range of model years, engine displacement, engine horsepower, and curb weight of three vehicle types are summarized. The vehicle sample includes the seven most common manufacturers of light duty vehicles driven in the U.S., which are Chrysler, Ford, GM, Toyota, Honda, Nissan, and Volkswagen (34). The HEVs typically have the smallest engines but higher curb weight than PCs because of their traction batteries. PTs typically have the largest engines by displacement and horsepower and the heaviest curb weight. For each vehicle, there are typically over 12,000 seconds of valid quality assured 1 Hz data.

Data Analysis

Raw data from OBD and GPS were processed and analyzed. Data from the OBD are typically broadcast at a rate faster than 1 Hz and are interpolated to a 1 Hz frequency for time

alignment with 1 Hz GPS data. The alignment is determined by comparing the time trace of vehicle speed from the OBD with that inferred from changes in GPS position (35).

Quantifying Road Grade

Road grade is estimated based on the relative change in elevation versus horizontal distance traveled. Road grade is estimated for 0.1 mile segments of vehicle travel based on statistical analysis of 1 Hz position and elevation for each segment. The precision and accuracy of this method has been detailed and extensively evaluated elsewhere (22).

The effective acceleration is estimated based on acceleration and road grade (18):

$$a_e = a + 35.66 \times \frac{RG}{100}$$

a_e = effective acceleration, km/h per second

a = acceleration, km/h per second

RG = percent increase in elevation per unit distance (%)

To evaluate the vehicle power demand to help assess trends in acceleration and speed, vehicle specific power (VSP) is estimated. VSP is an estimate of engine power demand that takes into account changes in kinetic and potential energy, rolling resistance, and aerodynamic drag, is estimated based on 1 Hz speed, acceleration, and road grade (36):

$$VSP = v\left[1.1a + 9.81\left(\sin\left(\arctan\left(\frac{RG}{100}\right)\right)\right) + 0.132\right] + 0.000302v^3$$

VSP = vehicle specific power, kW/ton

v = speed, km/h

a = acceleration, km/h per second

RG = percent increase in elevation per unit distance (%)

The vehicle performance envelope is quantified with speed bins in 5 mph increments from 0 to 75 mph, plus a bin for all speeds over 75 mph. The range of acceleration in each bin is quantified based on the 2.5^{th} and 97.5^{th} percentiles of variability in 1 Hz acceleration, thereby enclosing a 95 percent frequency range of acceleration. These percentiles were selected to provide a stable indicator of high and low acceleration that represent realistically achievable performance.

Software was written in Visual Basic (VBA) within Microsoft Excel to process data files for individual vehicles, each of which contains second-by-second speed, acceleration, road grade. For each vehicle, the 95 percent frequency range of acceleration and effective acceleration is inferred for each speed bin. The software repeats this for each vehicle, resulting in an inter-vehicle distribution of 2.5^{th} and 97.5^{th} percentiles of acceleration, and effective acceleration, for each speed bin. These distributions indicate inter-vehicle variability in the performance envelope. The mean value, standard deviation, and 95% confidence interval of the mean is estimated for each of the 2.5^{th} and 97.5^{th} percentiles for each speed bin. Inter-vehicle variability is estimated for PC, PT, and HEV vehicle groups. The software enables a user to adjust the width of speed bins and specify other acceleration percentiles of interest

Evaluation of Potential Sources of Variability

Factors that might affect the performance envelope are evaluated. Some sources of variability are categorical, such as vehicle type, transmission type (i.e. manual, automatic), and whether road grade is considered (i.e. effective acceleration incorporating road grade versus acceleration independent of road grade). For categorical factors, the two independent sample T test is used (37). The average 2.5^{th} and 97.5^{th} percentiles of acceleration are each compared, for each speed bin, for pairwise combinations of PC, PT, and HEV vehicle groups, between automatic and manual transmissions within the PC and PT groups, and between effective acceleration versus acceleration for all vehicles.

Continuous factors that are possible sources of variability in the vehicle performance envelope were evaluated, including engine displacement, engine horsepower (hp), vehicle curb weight (W), and the ratio of horsepower to curb weight (hp/W). The evaluation is based on linear least square regression analysis (38). Linear regression was applied to data sets comprised of the selected percentile (2.5^{th} and 97.5^{th} percentile) of acceleration for each vehicle for each speed bin, based on appropriate stratification by vehicle type. For example, linear regression was applied to 97.5^{th} percentiles of acceleration with respect to engine displacement for each of 63 PCs, separately for each of 16 speed bins. The key results of interest include the coefficient of determination, R^2, and the slope. Based on whether R^2 and slope were statistically significant, and also taking into account their magnitude, a judgment was made as to whether the selected percentiles of acceleration were substantially influenced by the potential source of variability being evaluated.

Effect of Road Grade on Cycle Average Emission Rates

To assess the role of driving cycles and road grade as sources of variability in cycle average emission rates, comparisons are made for six observed real-world driving cycles with and without road grade. The six cycles include four non-freeway cycles and two freeway cycles with average speeds from 22 to 63 mph with road grades varying between -6% and 6% (39).

Each cycle is quantified with respect to the time distribution of VSP in terms of 14 VSP modes defined based on ranges of VSP (40). Emission rates for PCs are estimated based on measurements of 63 PCs using Portable Emissions Measurement Systems (PEMS) using the method of Frey et al. (33). The emission rates are stratified into the same 14 VSP modes as the cycle activity. Therefore, cycle average emission rates are based on the product of fraction of time of activity and emission rate for each mode, summed over the 14 modes.

To enable comparison of cycle averages with and without road grade, VSP is estimated for each second of each driving cycle data using actual road grade and, separately, assuming that road grade is 0. The difference between cycle average emission rates for each cycle with and without road grade is compared.

Framework for Evaluating Driving Cycles

The extent to which any driving cycle of interest includes performance comparable to the achievable performance envelope is evaluated by comparing the 2.5^{th} and 97.5^{th} percentiles of each speed bin for the driving cycle to that from the real-world data measured for vehicle types of interest. For this purpose, the performance envelopes of PCs and PTs are weighted according to their national vehicle population fractions (11).

TABLE III-1 Summary of Distributions of Engine Displacement,Engine Horsepower, and Curb Weight for Measured Passenger Cars, Passenger Trucks, and Hybrid Electric Vehicles

Characteristic	**Passenger Cars** n=63 1997 to 2013 model years				**Passenger Trucks** n=32 1998 to 2013 model years				**Hybrid Electric Vehicles** n=5 2006 to 2012 model years			
	Ave[a]	SD[b]	Min	Max	Ave	SD	Min	Max	Ave	SD	Min	Max
Engine Displacement (L)	2.4	0.6	1.4	3.8	4.0	1.0	2.2	5.4	1.9	0.9	1.3	3.3
Horsepower (hp)	160	34	101	301	240	68	135	385	140	63	76	231
Curb Weight (lb)	3040	331	2339	3591	4260	824	3030	5820	3240	571	2747	4050

a. *Ave = average.*
b. *SD = standard deviation.*

RESULTS

Results are given for vehicle characteristics, the acceleration and speed performance envelopes based on real-world data, potential factors affecting the performance envelope, the effect of road grade on cycle average emission rates, and comparison of standard driving cycles with the measured performance envelope.

Vehicle Characteristics

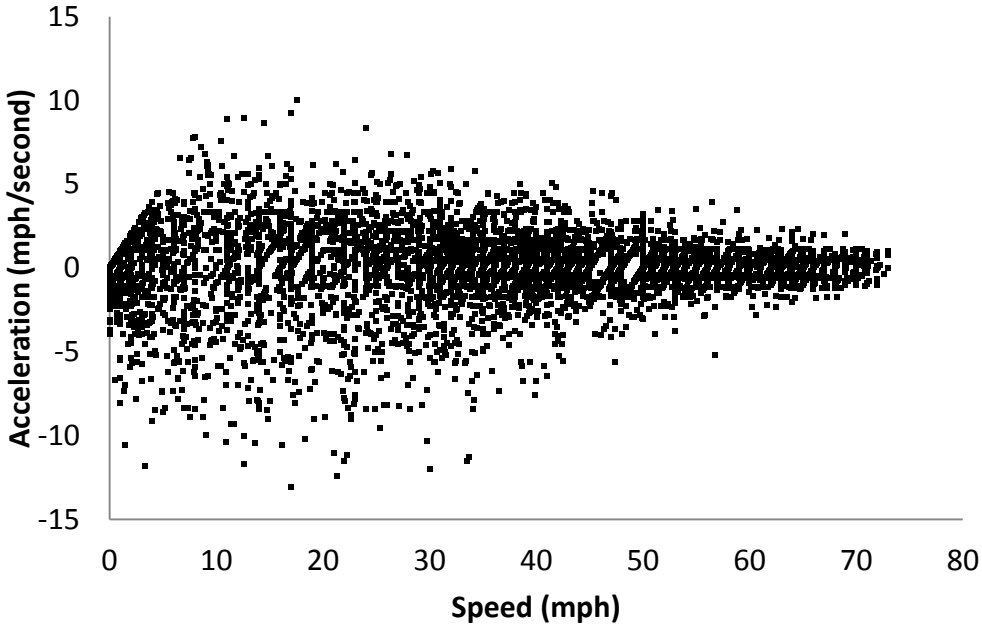
In Table 1, the sample size, range of model years, engine displacement, engine horsepower, and curb weight of three vehicle types are summarized. The vehicle sample includes the seven most common manufacturers of light duty vehicles driven in the U.S., which are

Chrysler, Ford, GM, Toyota, Honda, Nissan, and Volkswagen, and others (34). The HEVs typically have the smallest engines but higher curb weight than PCs because of their traction batteries. PTs typically have the largest engines by displacement and horsepower and the heaviest curb weight. For each vehicle, there are typically over 12,000 seconds of valid quality assured 1 Hz data.

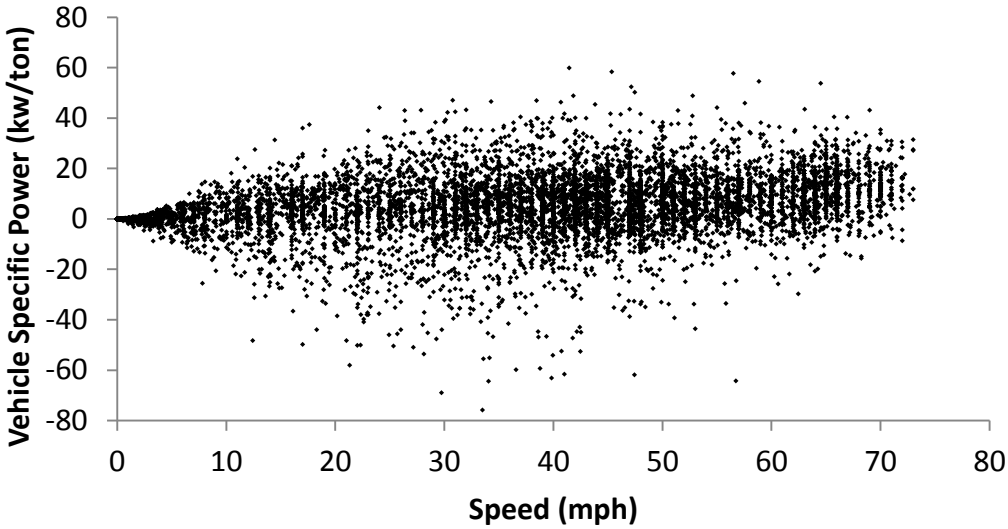
Joint Distribution of Acceleration and Speed

An example scatter plot of 1 Hz acceleration versus speed is given for one vehicle in Figure 1. There is a defined upper bound for acceleration for low speeds because the vehicle can accelerate from 0 mph to typically 1 to 5 mph in one second. Thus, for speeds of 0 to 5 mph, the highest achievable acceleration is of the same magnitude as the speed. It typically takes more than one second to reach speeds higher than approximately 5 mph, and thus the linear trend of the highest achievable acceleration does not extend to higher speeds. Conversely, a vehicle can decelerate to 0 mph from a wide range of speeds in the previous second, and therefore there is more scatter in the highest magnitude of deceleration at low speed.

Figure 1(b) depicts 1 Hz data for VSP versus speed. Except for a small proportion of data, the highest achieved VSP for speeds over 20 mph is approximately 25 kW/ton to 45 kW/ton. The scatter plot suggests that maximum VSP is approximately "constant" over a wide range of speed. Assuming that maximum achievable VSP is approximately constant, as speed increases, the maximum achievable acceleration must decrease, which is the trend observed in Figure 1(a). Thus, the trend of decreasing highest acceleration versus speed at speeds of about 10 mph to 20 mph or greater is the result of limitations of engine power output. The



(a) Joint Distribution of Acceleration and Speed



(b) Joint Distribution of Vehicle Specific Power and Speed

Figure III-1 Joint Distribution of Acceleration versus Speed, and Vehicle Specific Power versus Speed, for 2003 VW Passat, based on 11,573 seconds of 1 Hz data.

highest magnitude of decelerations are greater than the highest magnitude of decelerations because braking energy dissipation capability is higher than engine power output capability.

Vehicle Performance Envelopes

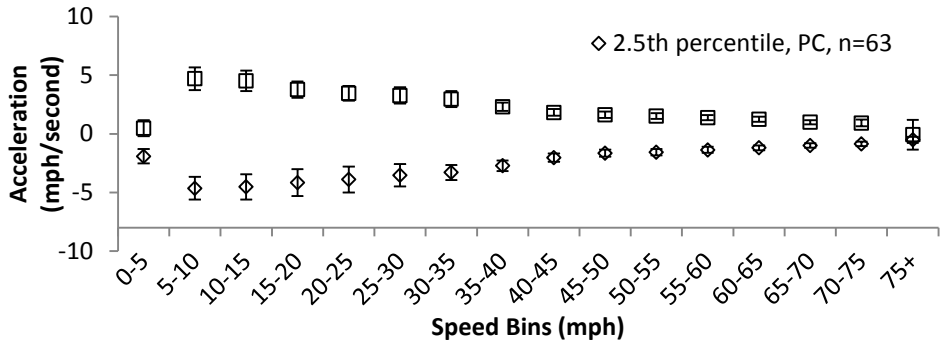
The performance envelopes for PC, PT, and HEV are given in Figures 2(a), 2(b), and 2(c), respectively. These envelopes are qualitatively similar to each other. Each indicates that the 97.5th percentile acceleration for the lowest speed bin is related to the speed reached in the first second of operation from a stop. The acceleration reached at 5 mph to 10 mph is approximately 5 mph/s for each of the three vehicle types, and typically declines monotonically to approximately 1 mph/s at speeds of 70 mph or higher. The inverse relationship between the high end acceleration and speed is constrained by engine power output limitations. The magnitude of decelerations are typically higher than the magnitude of accelerations, for a given speed range, similar to the observation for the individual vehicle of Figure 1. The confidence intervals depicted for the 2.5th and 97.5th percentiles of acceleration for each vehicle type and speed range illustrate that there is some inter-vehicle. However, for PCs and PTs, particularly at speeds over 35 mph, the 95 percent confidence intervals on the mean values of the 2.5th and 97.5 percentiles of acceleration are narrow, indicating consistency among the vehicles. The confidence intervals for the HEVs are wider because of much smaller sample size than for the other vehicle types.

Effect of Categorical Factors on Performance Envelope

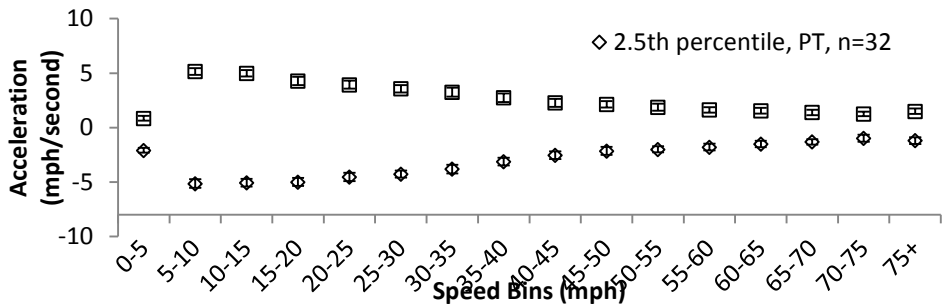
Based on the two sample T-test, no statistically significant difference was found for the 2.5th and 97.5th percentiles of acceleration for each speed range when comparing PC vs. HEV and

PT vs. HEV. This is in part because of the wider confidence intervals for the HEVs because of their smaller sample size. There were statistically significant differences in comparisons of PT vs. PC for speeds of 40 mph to 70 mph. Somewhat surprisingly, given their larger curb weight, the PTs had 97.5th percentiles of acceleration in this speed range that were 20% to 30% higher, on average, than for PCs. However, the magnitude of accelerations in this speed range are low, ranging from 1.8 mph/s to 1.0 mph/s for PC and 2.3 mph/s to 1.4 mph/s for PT.

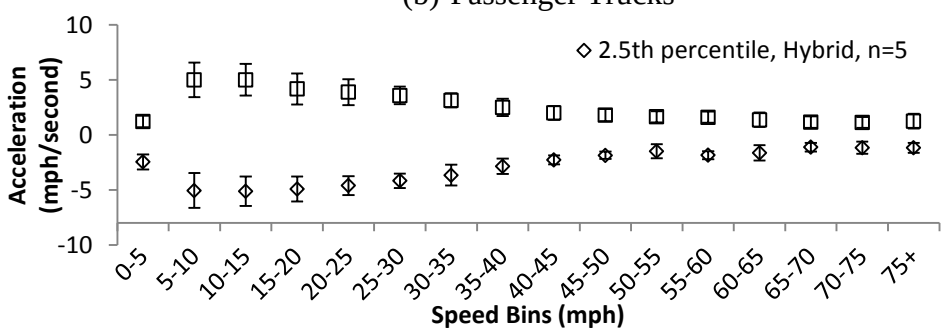
For PC and PT, comparisons were made for automatic versus manual transmission. There are only 8 PCs and 4 PTs with manual transmissions in the sample; thus, the comparison is affected by small sample size. Nonetheless, for PCs, the 97.5th percentile of acceleration for speeds of 0 to 10 mph were 30% higher for manual versus automatic transmissions. For PTs, the 97.5th percentile of acceleration is 30% lower for manual versus automatic transmissions for high speed ranges of 60 mph and higher. Overall, these results are deemed inconclusive given small sample size but the PC results are suggestive of higher performance capability of manual transmission vehicles.



(a) Passenger Cars



(b) Passenger Trucks



(c) Hybrid Electric Vehicles

Figure III-2. Vehicle Average Speed and Acceleration Performance Envelopes for Passenger Cars, Passenger Trucks, and Hybrid Electric Vehicles based on the 2.5th and 97.5th Percentiles of Acceleration for 16 Speed Ranges, with 95% Confidence Intervals

Based on all 100 vehicles, effective acceleration was found to be statistically significantly higher than acceleration for the 97.5th percentile of acceleration in speed ranges of 35 mph and higher.

Effect of Continuous Factors on Performance Envelope

There is not a statistically significant linear relationship between engine displacement and the 2.5th and 97.5th percentiles of acceleration for any speed bin, for either PCs or PTs. For HEVs, a linear relationship was found only for 15 mph to 20 mph but with an R^2 value lower than 0.1. Therefore, the overall finding is that there is not a significant effect of engine displacement.

For horsepower, no significant linear relationship was found for PCs. For PTs, statistically significant linear relationships were found for speeds of 15 mph to 65 mph, in which 97.5th percentile acceleration increased with horsepower. The regression slopes for the 97.5th percentile range from 0.002 to 0.007 mph/second per horsepower, with R^2 values of approximately 0.2. Overall, these findings are suggestive of weak sensitivity of the performance envelope to horsepower for PTs. For HEVs, statistically significant linear relationships were found for speeds of 10 mph to 40 mph.

For curb weight, there was no statistically significant effect found on the performance envelope for PCs. For PTs, the 97.5th percentile of acceleration was found to increase with curb weight in each speed bin from 15 mph to 65 mph, with R^2 values of approximately 0.2. However, curb weight is collinear with engine horsepower, and thus this trend may be more related to horsepower than curb weight. For HEVs, statistically significant linear

relationships were found for speeds ranging from 15 mph to 25 mph and from 45 mph to 50 mph. The 97.5th percentile of acceleration was found to increase with curb weight with R^2 values of approximately 0.1.

For the ratio of horsepower to curb weight (hp/W), there was no significant linear relationship found for the PC performance envelope. For PTs, the 97.5th percentile of acceleration was found to have a weak (R^2 ranging from 0.01 to 0.2) statistically significant increase with increase in the hp/W ratio for speeds ranging from 15 mph to 65 mph. For HEVs, the 97.5th percentile of acceleration increases with hp/W for speeds of 10 mph to 40 mph, with R^2 values of approximately 0.1. Thus, the power to weight ratio may be a weak factor.

Effect of Road Grade on Cycle Average Emission Rates

Cycle average emission rates of CO_2, NO_x, CO, and HC are compared with and without road grade for six real-world cycles in Table 2. The six cycles, which are subsets of the data used to estimate the performance envelop, are representative of real world driving on a range of road types and grades. The cycle average emission rates for NO_x and CO are more sensitive to road grade than for CO_2 and HC. The NO_x cycle average emission rates without road grade are as much as 9 percent higher. In contrast, the CO emission rates are as much as 8 percent lower. Cycle average CO emission rates tend to be sensitive to the amount of time spent at very high VSP mode, and thus the cycle average rates are lower when road grade is not considered. However, even though cycle average rates have only small sensitivity to road grade, the emission rates for localized segments within the cycles can have more

sensitivity. For example for segments with positive road grade, emission rates are typically underestimated, and for segments with negative grade, emission rates are typically overestimated, if grade is ignored (20, 22).

TABLE III-2 Cycle Average Emission Factors with Road Grade (RG) and Ignoring RG For Passenger Cars

		C_NF	1_NF	A	3	C_F	1_F
Average Speed (mph)		22.4	25.7	27.0	33.1	60.0	63.0
CO_2 (g/mi)	With RG	365	361	326	298	237	241
	Ignoring RG	368	357	325	297	243	242
	% Difference	**1%**	**-1%**	**0%**	**0%**	**2%**	**1%**
NO_x (g/mi)	With RG	0.19	0.19	0.18	0.16	0.13	0.13
	Ignoring RG	0.19	0.19	0.18	0.16	0.14	0.14
	% Difference	**3%**	**-1%**	**1%**	**3%**	**9%**	**3%**
CO (g/mi)	With RG	0.55	0.60	0.48	0.50	0.44	0.43
	Ignoring RG	0.54	0.55	0.46	0.46	0.42	0.42
	% Difference	**-1%**	**-8%**	**-4%**	**-8%**	**-4%**	**-3%**
HC (g/mi)	With RG	0.063	0.061	0.056	0.050	0.038	0.039
	Ignoring RG	0.064	0.060	0.056	0.050	0.039	0.039
	% Difference	**1%**	**-1%**	**0%**	**0%**	**2%**	**0%**

Evaluation of Driving Cycles Versus Performance Envelope

The performance envelope for four dynamometer driving cycles is compared in Figure 3 the real world observed performance envelope. The latter is weighted based on 58 percent PT and 42 percent PT to match the national population distribution of light duty vehicles (11).

As expected, given limitations on maximum acceleration, the FTP performance envelope is enclosed within the real-world performance envelope. The 95 percent frequency range of acceleration is smaller for the FTP, and the FTP has a maximum speed of only 57 mph. The HWFET has a similar frequency range of acceleration as the FTP and a similar range of speeds, but has higher average speed than the FTP. These comparisons illustrate that both

the FTP and HWFET are “mild” cycles that do not significantly challenge or exercise vehicle performance capability.

Although the range of speeds for the SC03 cycle are similar to those of the FTP and HWFET, the frequency range of accelerations is wider and is comparable to that of the real world performance envelope. In particular, the upper end of the frequency range, at the 97.5th percentile, is approximately the same as the real world performance envelope. This comparison implies that the SCO3 depicts a more realistic range of vehicle operation within the covered speed range than the FTP or HWFET.

Consistent with its reputation as an “aggressive” cycle, the US06 performance envelope has substantially wider frequency ranges than the real-world performance envelope. Acceleration in the US06 exceed 8 mph/s for some speed ranges, which is approximately 3 mph/s higher than for the real world performance envelope or the SC03. Thus, the US06 clearly challenges vehicle performance. Note that the 95 percent frequency range of the real world cycle does not define absolute minimum and maximum accelerations; therefore, it does not imply that a vehicle cannot produce a higher acceleration at a given speed than shown.

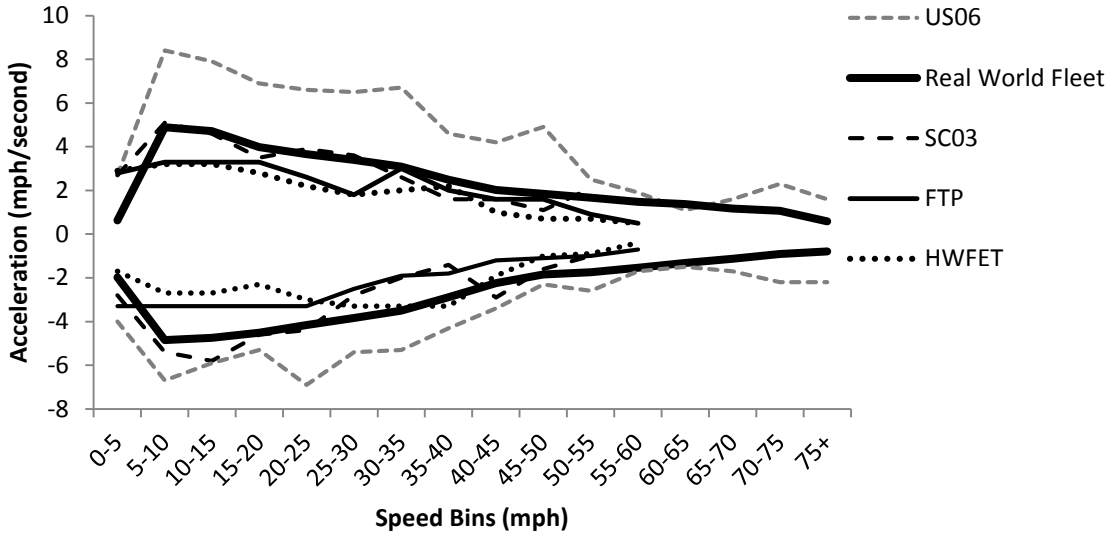


Figure III-3 2.5th and 97.5th percentile of acceleration for 16 speed bins for Real World data, and Federal Test Procedure (FTP) , US06, SC03, and Highway Fuel Economy Test (HWFET) driving cycles.

High Value for Data Series is the 97.5th Percentile of Acceleration and the Low Value is the 2.5th Percentile of Acceleration.

CONCLUSIONS

Based on the 95 percent frequency range of acceleration for a wide range of speeds, measured for 100 vehicles, the performance envelope was found to be approximately similar for PC, PT, and HEV vehicle types, with slightly wider ranges of acceleration at higher speeds for PTs. The consistency in the performance envelope suggests that it is possible to

identify typical values of high end acceleration associated with a particular speed, which in turn can be used either to calibrate or evaluate speed trajectories predicted by TSMs. The similarity of the performance envelops among the measured vehicles implies that a reasonable estimate of the performance envelope can be obtained based on a small sample of vehicles.

The method used here to quantify the performance envelope for real world data can also be applied to simulated 1 Hz trajectories from TSMs to enable comparisons and determination of whether TSM simulated trajectories are realistic. Cycle average emission rates are sensitive to differences in driving cycles, as shown in Table 2, and thus it is important that TSM simulated trajectories be realistic.

The real-world performance envelope was found to be weakly different for PT versus PC, but the absolute differences in the high end accelerations between these vehicle types were relatively small. Qualitatively, the results were similar for all three vehicle types.

The results provide weak or suggestive evidence that factors such as transmission type, road grade, and horsepower may affect the performance envelope. Horsepower and curb weight are positive correlated. For PTs, the performance envelope was found to be weakly significantly sensitive to horsepower, curb weight, and the ratio of hp/W; most likely, the hp/W ratio is the most useful explanatory factor and its role in affecting the performance envelope should be further explored.

Road grade has a weak effect on cycle average emission rates, which is consistent with prior studies, but can have a significant effect for road segments that have only positive or negative grades.

Based on this method, and consistent with previous findings, the FTP and HWFET are shown to be well-enclosed within the performance envelope and thus do not include high engine loads. The SCO3 performance envelope is approximately the same as that of the real world data over the range of speeds included in the SC03. In contrast, the US06 is clearly an "aggressive" cycle that requires exercising a vehicle well beyond the typical 95 percent frequency ranges of acceleration obtained from field measurements in this work.

The real world performance envelope was measured based on low to moderately priced production cars. No high performance "supercars" were included in the sample. Furthermore, the data developed here did not include motorcycles, or large trucks. Performance envelops are likely to be different for these other vehicle types compared to the PC, PT, and HEV vehicles measured here.

Real-world measurements are subject to uncontrollable traffic and weather conditions that might limit observed vehicle performance at a given location or time period. However, the consistency of results across the 100 vehicles may imply that occasional traffic incidents, work zones, traffic congestion, and so on did not significantly affect results. Future work to assess whether driving behavior may limit the observable performance envelop is recommended.

ACKNOWLEDGMENTS

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PART IV DEVELOPMENT AND EVALUATION OF A SIMPLIFIED VERSION OF MOVES FOR COUPLING WITH A TRAFFIC SIMULATION MODEL

ABSTRACT

The MOtor Vehicle Emission Simulator (MOVES) released in 2009 by the U.S. Environmental Protection Agency is an empirically based modal model capable of estimating project level on road vehicle emission rates for a wide variety of driving cycles. Many researchers and practitioners are attempting to combined MOVES with travel demand models (TDMs) and traffic simulation models (TSMs) for the purpose of estimating emissions impacts of possible future changes in road infrastructure, vehicle mix, traffic control measures, and other factors. However, MOVES is a computationally intensive model, and direct dynamic coupling of MOVES to a TDM or TSM can be impractical. To facilitate the capability to estimate link-based emission factors based on second-by-second vehicle speed trajectories, a simplified version of MOVES is demonstrated here. A Cycle correction factor (CCF) is generated for a selected vehicle type and driving cycle based on distribution of time spent in each of 23 operating mode bins. Operating modes are defined by the instantaneous speed and Vehicle Specific Power (VSP). The emission factors estimated by the simplified model are demonstrated to be sensitive to differences between driving cycles with similar average speeds. The errors of the simplified model cycle average predictions are within ±1% for 92% of the cases among pollutants, ages, and driving cycles, for passenger cars, passenger trucks, light commercial trucks, single unit short haul trucks, and combination long haul trucks. The application of the simplified model is demonstrated based on empirical driving cycles observed from field measurements.

INTRODUCTION

Mobile source emissions contribute significantly to overall air pollution in the United States. An accurate assessment of motor vehicle emissions is essential for effective air quality management (*1*). Emissions factor models quantify the relationship between vehicle characteristics, vehicle dynamics (e.g., speed and acceleration), roadway infrastructure (e.g., road grade) and emissions at multiple scales (*2*). To estimate vehicle emissions inventories, vehicle activity data are needed, such as traffic volume, fleet mix, ambient conditions, fuel type, and speed. Traffic volume and vehicle speed can be quantified based on traffic detectors. Travel demand models (TDMs) and traffic simulation models (TSMs) can provide more spatial coverage of estimated vehicle activity, and can be used to evaluate what-if strategies regarding future transportation improvement projects (TIPs) or traffic control measures (TCMs). TDMs typically quantify link-based average speeds based on groups of vehicles on a link-by-link basis. TSMs estimate individual vehicle speed trajectories based on car-following and lane-changing theories (*3*).

Modeling Vehicle Emissions

Various TDMs and TSMs have in-built capabilities to estimate vehicle emissions (*4*). However, the most rigorous vehicle emissions models are standalone software, including driving cycle and modal models (*5*). Driving cycle models estimate emissions based on cycle average speed and other variables such as vehicle fleet, vehicle age, fuel consumption and climate. An example is MOBILE6 (*6*). Modal models, such as MOVES and the Comprehensive Modal Emissions Model (CMEM), estimate vehicle emissions based on

estimates of engine load that depend on high resolution data regarding the vehicle speed trajectory (*7, 8, 9*).

MOVES estimates emissions for highway vehicles for CO_2, CO, NO_x, hydrocarbons, and others, at multiple spatial scales (*10*). MOVES is based on second-by-second measurements of vehicle emissions that are divided into "Operating Mode (OpMode) bins (*11*)." Except for braking and idling, the OpMode bins are stratified by speed ranges (up to 25 mph, 25 to 50 mph, and over 50 mph) and by Vehicle Specific Power (VSP) (*12*). VSP is an estimate of engine load based on vehicle speed, acceleration, and road grade. The OpMode bins are weighted based on time spent in each bin to represent any driving cycle. The multiple scales of analysis include national, county and project. For project scale analysis, a user can enter link-based average speeds or second-by-second "driving schedules" that include vehicle speed and road grade. Thus, the project scale feature of MOVES is conceptually compatible with the typical output of either a TDM or TSM.

The OpMode bin emission rates for each vehicle technology in the MOVES default database represent a base scenario of conditions for temperature, humidity, air conditioning load, fuel properties, and other factors. MOVES adjusts the default emission rates to represent user specific values of these factors (*13*).

Vehicle emissions depend not just on cycle average speed but with other factors influenced by driving behavior. Estimated emissions are influenced by acceleration (*5*). For the same average speed, emission rates are higher if there is transient variability in speed versus driving at constant speed (*14*). For example, the estimated emission factors at a

constant speed of 40 mph for CO_2, NO_x, HC, and CO are lower by 14%, 36%, 49%, and 23%, respectively, compared to transient operations at the same average speed. Modal models can account for such differences.

Challenges and Opportunities in Coupling Vehicle Activity and Emissions Models

One of the main challenges in combining MOVES with either a TDM or a TSM is that MOVES is computationally intensive. A typical study network might contain thousands of links, each of which would be represented by a link-based average speed (mesoscopic) or driving schedule (microscopic).

TDMs or TSMs are typically applied to case studies that represent a narrow period of time on a particular type of day, such as peak morning or afternoon travel on a weekday (*15, 16*). Thus, vehicle fleet mix and fuel properties are likely to be approximately constant for the simulation time period. Although ambient temperature may lead to second-order effects on emissions of some pollutants, such as NO_x, CO, and hydrocarbons, these effects are typically not the focus of TIPs and TCMs. TIPs and TCMs are typically focused on modifying vehicle dynamics, such as by improving traffic signal timing, traffic flow, or incident response. The main goal of emissions estimation in this context is to provide an appropriate estimate of the relative change in emissions as a result of controllable factors.

Because many of the factors to which MOVES is sensitive are approximately constant during the time period of a typical TDM or TSM simulation, there is no need to run MOVES in its entirety for every link in a network. Furthermore, because MOVES estimates

emission factors based on weighted combinations of OpMode bins, a similar approach can be used as part of a simplified model that can be directly coded as part of a TDM or TSM (*17*).

Research Questions

The key research questions addressed here are: (1) can a simplified reduced form version of MOVES provide accurate estimates of relative changes in cycle average emission rates for a range of pollutants and vehicle types?; (2) how sensitive are cycle average emission rates to variations in driving cycles based on factors such as average speed and road type?; and (3) what are the implications for implementation and use of a simplified version of MOVES with TDMs or TSMs?

METHODOLOGY

The concept for the simplified version of MOVES is to quantify link-based or cycle-average emission rates based on vehicle speed trajectories and road grade, without the computational overhead for factors that remain approximately constant over a multi-hour simulation. Thus, fuel properties, ambient conditions, inspection and maintenance (I/M) program, and other factors are held constant. The key parameters of the simplified model are calibrated based on default data used as input to MOVES and from a base emission rate obtained from MOVES. The calibrated simplified model is applied to verification case studies for driving cycles that correspond to default driving schedules in MOVES. The performance of the simplified model is evaluated based on the prediction error compared to MOVES for the selected cycles. The simplified model is demonstrated for an example case study.

Modal Emission Model

The MOVES definition of VSP is based on coefficients that are used in setting up chassis dynamometer tests. The coefficients include rolling resistance, rotational resistance, and aerodynamic drag (*18, 19*):

$$\mathrm{VSP} = (\mathrm{A} \times \mathrm{V_t} + \mathrm{B} \times \mathrm{V_t^2} + \mathrm{C} \times \mathrm{V_t^3} + \mathrm{m} \times \mathrm{V_t} \times \mathrm{a_t})/\mathrm{m} \qquad \text{(Equation 1)}$$

Where,

VSP	= vehicle specific power, kW/tonne
V_t	= speed at time t, m/s
a_t	= acceleration at time t, m/s^2
A	= rolling resistance coefficient, kW-sec/m
B	= rotational resistance coefficient, $kW\text{-}sec^2/m^2$
C	= aerodynamic drag coefficient, $kW\text{-}sec^3/m^3$
m	= vehicle mass, tonne.

The coefficients A, B, C, and m vary among vehicle types. For example, for a passenger car, A=0.1565 kW-sec/m, B=2.002×10^{-3} $kW\text{-}sec^2/m^2$, C=4.926×10^{-4} $kW\text{-}sec^3/m^3$, and m=1.479 tonne. Although road grade is also a factor in VSP, it is not included in Equation (1) because the default driving schedules used in MOVES are assumed to have zero

grade. However, MOVES quantifies VSP based on road grade for user-entered driving cycles.

The simplified model estimates tailpipe running exhaust emissions. For tailpipe exhaust emissions, there are 23 OpMode bins. The OpMode bins represent deceleration, idle, and three speed ranges as defined in **Error! Reference source not found.**. Within each peed range, there are multiple bins defined based on VSP. VSP has been shown to be highly correlated with fuel use (*11*). For a given vehicle technology, age, and pollutant, the OpMode bin emission rates are obtained from the MOVES default input database in units of grams per hour.

Methods for Linking Emissions and Traffic Models

There have been numerous efforts to incorporate vehicle emissions models directly into TDMs or TSMs, or to manually pass data from TDMs or TSMs to a separate vehicle emissions model. A few illustrative examples are briefly discussed. For example, Advanced Interactive Micro-Simulation for Urban and Non-Urban Networks (AIMSUN) is a TSM with a simple vehicle emissions model that estimates tailpipe emissions of CO_2, NO_x, particulate matter less than 10 microns in aerodynamic diameter (PM_{10}) and volatile organic compounds (VOC) based on a non-linear regression function of instantaneous speed and acceleration (*20*). Total emissions are based on integrating instantaneous emissions along vehicle trajectories for all simulated vehicles (*21*). AIMSUN has been used in combination with a European modal emissions model, VERSIT+ (*22, 23*).

The TRansportation ANalysis and SIMulation System (TRANSIMS), a TSM, and EMME/2, a TDM, have been used with MOBILE6 to evaluate differences in emissions predictions between them, based on case studies for Portland, Oregon (*24*). The emissions estimated based on TRANSIMS simulation were lower than those based on EMME/2 for freeways and higher for arterials, because of differences in assignment of vehicles between these road types.

MOBILE6 has been used with other TSMs, such as PARAMICS, to estimate the emissions impact of Electronic Toll Collection (ETC) plazas versus traditional toll collection. MOBILE6 emission factors for selected cycle average speeds were imported into PARAMICS. Toll plaza emissions were estimated to be reduced in the short-term as a result of ETC but to increase in the long term because of growth in traffic flow (*4*).

MOVES has been used in combination with several TSMs, including PARAMICS, Dynamic Urban Systems for Transportation (DynusT), and VISSIM. PARAMICS was used to estimate link volume and average speed as input to MOVES to compare alternative transportation fuels (*26*). DynusT was used to generate link-by-link input data for MOVES for a simulation of downtown Sacramento, CA (*27*).

VISSIM was used with MOVES to estimate vehicle activity for the West 3rd Ring Road expressway in Beijing, China (*28*). The distribution of second-by-second VSP and the fraction of time spent in each of the MOVES OpMode bins were estimated based on simulated and measured vehicle activity data. Apparent errors in the simulated activity, in comparison to measured activity, could not be significantly reduced by adjusting VISSIM

calibration parameters. Emissions models may be sensitive to microscopic aspects of estimated TSM vehicle activity that are not yet well predicted nor well validated.

VISSIM has been used with MOVES to evaluate the emissions impacts of Connected Vehicle (CV) technology, which enable short range communication between CV vehicles and road side units, and the impact of signal optimization to reduce emissions at a specific high emissions location within a PM nonattainment area (*29, 30*). VISSIM has been used with CMEM, based on development of software to automatically transfer VISSIM output to CMEM input. However, the run-time of the coupled VISSIM-CMEM model was significantly higher than for VISSIM alone (*31*).

Dynamic linkage of traffic and emissions models is challenging and can lead to significantly longer run times. Thus, development of a simplified emissions model that can be directly incorporated into a TDM or a TSM is likely to lead to faster run times. Here, we focus on the challenge of developing a simplified model for estimating emissions.

Conceptual Model

The simplified model contains: (1) a base emission rate that accounts for site-specific characteristics such as fuel type, ambient temperature, and I/M program; and (2) a cycle correction factor that accounts for speed trajectories and OpMode bin emission rates. The speed trajectories can be obtained from empirical data or from predictions of a TSM. The simplified model includes multiple vehicle types and ages. The approach can be adapted to a TDM by mapping link-average speed to a driving schedule, from which a distribution of

OpMode bins can be inferred (*32*). Thus, the cycle average emission rate for a pollutant for any link or vehicle speed trajectory for a fleet of vehicles is given by

$$CE_{p,c} = \sum_v \left\{ \left[\sum_a (EF_{p,b,a,v} \times CCF_{p,c,a,v} \times f_{a,v}) \right] \times f_v \right\} \qquad \text{(Equation 2)}$$

Where,

$CE_{p,c,}$ = cycle average emission factor for any arbitrary driving cycle c, for pollutant p, for a fleet of vehicles with mixed types and ages, gram/mi

$ER_{p,b,a,v}$ = base emission rate for base cycle b, age a, vehicle type v, and pollutant p, gram/mi

$CCF_{p,c,a,v}$ = cycle correction factor for driving cycle c, age a, vehicle type v, and pollutant p

$f_{a,v}$ = age fraction for age a and vehicle type v

f_v = vehicle type fraction for vehicle type v

c = cycle c

b = base cycle

p = pollutant

The Base Emission Rate (BER) ($EF_{p,b,a,v}$) can be estimated for any arbitrary driving cycle chosen as a base cycle. The Federal Test Procedure (FTP) is the basis for U.S. emissions certifications testing, and is selected here (*33*). The numerical value of the base emission rate is obtained for a given pollutant, vehicle type and age by running MOVES

using the project level feature, and entering the second-by-second driving cycle for the base cycle.

The Cycle correction factor (CCF) is the ratio of the emission rate for any cycle to that of the base cycle. For each of the selected and base cycles, the fraction of time in each MOVES OpMode bin must be estimated based on the driving schedule. Since the BER is in grams per mile, the cycle average speed in miles per hour for the base and selected cycles are used to convert from grams per second from the default database to grams per hour:

$$\mathrm{CCF}_{p,c,a,v} = \left(\frac{\left(\sum_m f_m^c \times \mathrm{ER}_{p,a,v,m}\right)}{\left(\sum_m f_m^b \times \mathrm{ER}_{p,a,v,m}\right)} \right) \left(\frac{V^b}{V^c} \right) \qquad \text{(Equation 3)}$$

Where,

$\mathrm{ER}_{p,a,v,m}$ = default emission rate for pollutant p, age a, vehicle type v, in operating mode bin m, gram/hour

$f_m{}^c$ = fraction of time in OpMode bin m in cycle c

$f_m{}^b$ = fraction of time in OpMode bin m for base cycle b

V^c = cycle average speed for cycle c, mph

V^b = cycle average speed for base cycle b, mph

Some vehicle types, such as passenger trucks (PTs), light commercial trucks (LCTs), single unit short haul trucks (SHTs), and combination long-haul trucks (LHTs), have two or more "regulatory classes" in the MOVES default database. A regulatory class is a subcategory of a vehicle type based on Gross Vehicle Weight (GVWR). For example, LHTs are comprised of 5% of regulatory class 46 (Medium Heavy Duty, 19.5K lbs < GVWR <=33K lbs) and 95% of regulatory class 47 (Heavy Heavy Duty, GVWR > 33K lbs). These nationwide percentages of the distribution of regulatory classes are obtained from MOVES default database. The default regulatory class contributions were used in the simplified model, and cycle average results for CO_2, NO_x, CO, and HC were compared to MOVES for PT, LCT, SHT, and LHT. The results for SHT and LHT, as detailed later, were comparable. However, the difference between the two models for some pollutants for PT and LCT were higher than expected. Therefore, a sensitivity analysis of cycle average emission rates with respect to regulatory class fraction was conducted for these two vehicle types.

The fraction of time in each OpMode bin for a given cycle is estimated by calculating VSP for each second based on speed, acceleration, grade, and vehicle type. Each second is binned into an OpMode according to definitions in TABLE IV-1.

The MOVES default data for operating mode bin emission rates are based on default values of fuel properties and ambient condition. MOVES uses correction factors to adjust for differences in factors such as ambient temperature, and humidity (*13*). Thus, when calibrating the simplified model, their factors are taken into account when estimating Base Emission Rate from one MOVES run Some factors only affect BER and not CCF, e.g.

temperature alone, or humidity alone. However, some factors, such as air conditioning, affect various operating mode bins differently. As part of ongoing work, efforts are being made to identify adjustments, such as for air conditioning, that have different value depending on the operating modes.

Verification of the Simplified Model

The simplified model is verified based on comparisons to MOVES predictions for selected driving cycles. For PCs, PTs, and LCTs, MOVES uses 18 default cycles with average speeds from 2.5 to 76 mph. MOVES uses 11 default cycles with average speeds from 5.8 to 71 mph for heavy duty vehicles including SHTs and LHTs, and 14 default cycles with average speeds from 4.6 to 73 mph for TBs (*18, 34*). These cycles are used to estimating emission rates in the national and county level analysis modes, or when a user enters a link average speed in the project level analysis mode. Thus, these cycles are a convenient basis for comparisons of the simplified model to MOVES.

To assess the robustness of the simplified modeling approach, the approach is applied to PCs, PTs, LCTs, SHTs, LHTs, and TBs, each for vehicle ages of 0, 5, 10, and 15 years based on calendar year 2011. The six vehicle types selected here comprise more than 95% of the vehicles in the fleet. The approach is applied to estimate emission rates for CO_2, NO_x, CO, and hydrocarbons (HC).

RESULTS

Results are given in detail for PCs to illustrate the method and performance of the simplified model. Results for the other selected vehicle types are summarized. The default OpMode

average emission rates for gasoline PCs are given in TABLE 1. The OpMode average emission rates increase as VSP increases within a particular speed range. There is substantial variability in the modal emission rates. The ratio of the highest to lowest modal average emission rates are 15.5 for CO_2, 313 for NO_x, 2,000 for CO, and 225 for HC.

PC default driving cycles are summarized in TABLE 2. There are 9 freeway cycles, 7 non freeway cycles and 2 cycles representing both freeway and non freeway. Variability in the distribution of time among OpModes can affect cycle average emission rates. As illustrative examples, the fraction of time in each OpMode for selected cycles is given in TABLE 3. Cycle 101 has the lowest average speed of 2.5 mph, and a maximum instantaneous speed of only 10 mph. This cycle is comprised only of OpModes 0, 1, 11, 12, and 13. In contrast, the instantaneous speeds of Cycle 1026 vary from 6.7 mph to 70.8 mph, and this cycle is comprised of most of the OpModes. Cycles 1020 and 1019, and the FTP, also have wide ranges of instantaneous speed. Cycle 1009 represents high speed operation with instantaneous speeds ranging from 60.5 mph to 80.4 mph. Thus, Cycle 1009 covers only the high speed OpModes.

Cycle Correction Factors

As an example of the relative variation in emission rates with respect to cycle average speed, CCFs for five year old gasoline PC are shown in TABLE 4. For each pollutant, the highest CCF occurs at Cycle 101 (average speed of 2.5 mph). The CCFs tend to decrease as average speed

TABLE IV-2 Example of Default Operating Mode Bin Average Emission Rates in the MOVES Model for Selected Pollutants: Passenger Cars, Gasoline, Five Years Old.

Operating Mode ID[b]	Operating Mode Description		Default Average Emission Rate (g/hr) for 5 Year Old Gasoline Passenger Cars[a]			
			CO_2[c]	NO_X	CO	HC
0	Braking[d]		3529[f]	0.23	5.14	0.19
1	Idling[e]		3265	0.10	0.89	0.05
11	VSP< 0	1≤Speed<25	5134	0.34	17.69	0.13
12	0≤VSP< 3		7089	0.52	28.88	0.10
13	3≤VSP< 6		9852	1.22	26.62	0.19
14	6≤VSP< 9		12449	2.15	38.20	0.26
15	9≤VSP<12		14845	3.81	55.39	0.36
16	12≤VSP		17930	7.94	93.47	0.58
21	VSP< 0	25≤Speed<50	6985	0.67	23.05	0.20
22	0≤VSP< 3		7950	1.09	30.55	0.18
23	3≤VSP< 6		9683	1.65	39.28	0.20
24	6≤VSP< 9		12423	2.79	57.42	0.38
25	9≤VSP<12		16578	3.91	65.17	0.37
27	12≤VSP<18		21855	6.16	97.87	0.59
28	18≤VSP<24		29459	13.54	239.24	3.84
29	24≤VSP<30		40359	23.78	506.67	6.81
30	30≤VSP		50682	31.29	1779.51	11.25
33	VSP< 6	50≤Speed	9951	1.44	17.31	0.19
35	6≤VSP<12		15956	3.96	29.56	0.27
37	12≤VSP<18		20786	5.54	43.51	0.34
38	18≤VSP<24		27104	11.50	219.28	2.59
39	24≤VSP<30		36102	17.12	231.37	3.76
40	30≤VSP		46021	21.56	679.99	4.92

[a] The number of significant figures shown here is based on the data reported in the MOVES default database. The data are not likely to be as precise as implied by the number of significant figures contained in the default database.

TABLE IV-1 Continued

[b] Operating Mode ID refers to operating mode bins that represent braking (ID = 0), idling (ID=1), and varying levels of speed and vehicle specific power.

[c] CO_2 emission rates are estimated based on modal energy consumption reported in the MOVES default database and default fuel properties used in MOVES for gasoline.

[d] Braking is defined as the acceleration is less than or equal to -2 mph/sec, or the accelerations of continuous three seconds are all less than or equal to -1 mph/sec. Let a(i), a(i-1), a(i-2) be the accelerations of ith, $(i-1)^{th}$, $(i-2)^{th}$ seconds respectively. Braking is defined as $a(i) \leq -2$ mph/sec, or $a(i) \leq -1$ mph/sec and $a(i-1) \leq -1$ mph/sec and $a(i-2) \leq -1$ mph/sec.

[e] Idling is defined as the speed is larger than or equal to -1 mph and less than 1 mph. Let v(i) be the speed of ith second. Idling is defined as $-1 \text{ mph} \leq v(i) < 1 \text{ mph}$.

[f] The Operating Mode emission rates for PT, LCT, SHT, and LHT are weighted by emission rates for regulatory classes and the fractions of regulatory class of each vehicle type. The fractions are obtained from MOVES default database (*25*).

TABLE IV-3 Summary of Default Freeway and Non-Freeway Driving Cycles Used in the MOVES Model for Passenger Cars, Passenger Trucks and Light Commercial Trucks

Driving Schedule ID in Default Database	Travel Time (second)	Average Speed (mph)	Road Type (F=Freeway; N=Non-Freeway)
101	601	2.5	F
1033	852	8.7	F
1043	869	15.7	F
1041	708	18.6	N
1021	904	20.6	F
1030	512	25.4	N
153	455	30.5	F
1029	753	31.0	N
1026	912	43.3	N
1020	972	46.1	F
1011	680	49.1	N
1025	800	52.8	N
1019	729	58.8	F
1024	886	63.7	N
1018	904	64.4	F
1017	518	66.4	F
1009	568	73.8	F, N
158	580	76.0	F, N
FTP[a]	1874	21.2	F, N

[a] FTP is not a default cycle in MOVES. It is selected as base cycle in the case study to calculate base emission rates.

increase, reaching a minimum value at approximately 60 mph for CO_2 and CO and at 21.2 mph for NO_x and HC. The CCFs do not vary exactly monotonically with average speed, since factors other than average speed, such as the number of stops or the fraction of time in different speed or VSP ranges, also affect cycle average emission rates. The ratios of the highest to lowest CCFs are 6.5, 2.0, 4.5, and 3.0 for CO_2, NO_x, CO, and HC respectively, which implies that there is substantial variability in cycle average emission rates among the selected cycles.

For Cycle 1021 versus the FTP, which has similar average speeds of approximately 20 mph, the CCFs for all pollutants are 2% to 25% higher. The fraction of time spent in OpModes with VSP higher than 12 KW/ton for Cycle 1021 is 9% higher, on a relative basis, than for the FTP. For Cycles 153 and 1029, which have similar average speeds, Cycle 1029 has higher CCFs. The fraction of time spent in OpModes with VSP higher than 12 KW/ton for Cycle 1029 is 23% higher, on a relative basis, than for Cycle 153. Cycles 1024, 1017 and 1018 have similar average speeds. However, the NO_x and CO CCFs for Cycle 1017 are 10% and 18% higher, respectively, than for Cycle 1018 and are 9% and 7% higher, respectively, than for Cycle 1024. Among these three cycles, Cycle 1017 has the highest fraction of time with speeds over 50 mph.

TABLE IV-4 Examples of the Fraction of Time in Each Operating Mode Bin for Selected Default Driving Cycles for Passenger Cars, Passenger Trucks, and Light Commercial Trucks

Operating Mode ID	Fraction of Time in Operating Mode Bin by Driving Schedule ID and Cycle Average Speed[a]						
	101 (2.5 mph)	1021 (20.6 mph)	1026 (43.3 mph)	1020 (46.1 mph)	1019 (58.8 mph)	1009 (73.8 mph)	FTP (21.2 mph)
0	0.015	0.066	0.065	0.078	0.030	0.002	0.118
1	0.502	0	0.000	0.003	0	0	0.196
11	0.153	0.063	0.063	0.043	0.008	0	0.051
12	0.326	0.057	0.057	0.060	0.003	0	0.089
13	0.003	0.024	0.024	0.042	0.004	0	0.067
14	0	0.016	0.016	0.011	0.005	0	0.044
15	0	0.007	0.007	0.009	0	0	0.023
16	0	0.009	0.009	0.005	0	0	0.011
21	0	0.055	0.055	0.030	0.029	0	0.046
22	0	0.055	0.055	0.025	0.021	0	0.105
23	0	0.056	0.056	0.027	0.029	0	0.101
24	0	0.047	0.047	0.028	0.044	0	0.027
25	0	0.049	0.049	0.024	0.023	0	0.018
27	0	0.047	0.047	0.025	0.023	0	0.014
28	0	0.010	0.010	0.005	0	0	0.007
29	0	0.002	0.002	0.002	0	0	0
30	0	0	0.000	0	0	0	0
33	0	0.124	0.124	0.111	0.117	0.046	0.027
35	0	0.110	0.110	0.211	0.229	0.171	0.038
37	0	0.134	0.134	0.181	0.294	0.342	0.014
38	0	0.048	0.048	0.050	0.108	0.289	0.002
39	0	0.019	0.019	0.020	0.025	0.130	0
40	0	0.004	0.004	0.010	0.008	0.021	0

[a] Numbers may not add exactly to 1.000 due to rounding.

Comparison of Simplified Model and MOVES for Passenger Cars

The cycle average emission factors from the simplified model and from MOVES are compared in TABLE 5 for five year old gasoline PCs. The differences between them are within $\pm$0.5% for all cycles and pollutants. The errors of the cycle average emission factors are within $\pm$0.6% for all cycles, pollutants, and ages. The PC emission factors in grams per mile for all pollutants have a maximum value at the lowest cycle average speed of 2.5 mph, and vary substantially with cycle average speed and with respect to the OpMode distribution among cycles with similar average speeds. The minimum value of the emission factors are at approximately 50 mph for CO_2 and CO and typically at 21 mph for NO_x and HC.

The base emission rate $EF_{p,b,a,v}$ is calibrated based on running MOVES for the same base case conditions. MOVES takes into account humidity and other adjustments such as temperature, air conditioning, and I/M program. Thus, $EF_{p,b,a,v}$ is the quantify via which the simplified model can be calibrated to a particular set of ambient and operational conditions for a given case study.

TABLE IV-5 Cycle correction factors (CCFs) for Five Year Old Gasoline Passenger Cars for Default Driving Cycles and Base Emission Rate

Cycle ID	Average Speed (mph)	Cycle correction factor (CCF)			
		CO_2	NO_X	CO	HC
101	2.5	4.97	1.68	4.02	3.18
1033	8.7	1.81	1.52	1.71	1.95
1043	15.7	1.28	1.17	1.33	1.29
1041	18.6	1.21	1.47	1.77	1.73
1021	20.6	1.08	1.02	1.25	1.12
FTP[a]	21.2	1.00	1.00	1.00	1.00
1030	25.4	1.02	1.39	1.30	1.44
153	30.5	0.893	1.09	1.10	1.06
1029	31.0	0.904	1.27	1.29	1.40
1026	43.3	0.819	1.23	0.980	1.15
1020	46.1	0.820	1.27	0.931	1.11
1011	49.1	0.803	1.33	0.927	1.24
1025	52.8	0.789	1.31	0.953	1.19
1019	58.8	0.766	1.29	0.887	1.11
1024	63.7	0.781	1.42	1.03	1.32
1018	64.4	0.775	1.40	0.939	1.28
1017	66.4	0.792	1.49	1.08	1.46
1009	73.8	0.830	1.77	1.37	2.02
158	76.0	0.881	2.02	1.97	2.58

[a] FTP is used as the base cycle. Thus, by definition, the cycle correction factor for the FTP is 1.00 for all pollutants.

Comparisons between Simplified Model and MOVES for Other Vehicle Types

Results were obtained for 0, 5, 10, 15 year old PTs, LCTs, SHTs, LHTs, and TBs,each for CO_2, NO_x, CO, and HC. For PTs and LCTs, the general trends in the results are similar to

those for PCs. The CO_2, CO, and HC emission factors are highest at the lowest cycle average speed, decrease as the cycle average speed increase, reach a minimum value around 60 mph, then increase. NO_x emission factors have a minimum value at approximately 20 mph. Using the MOVES default regulatory class fractions for PTs and LCTs in the simplified model, the cycle average emission factors were typically within 0.3% of the MOVES estimates for CO_2, but the differences increased to 10 to 15 percent among NO_x, CO, and HC depending on the cycle. Based on sensitivity analysis of the regulatory class distribution, the differences between the simplified model and MOVES results are between -3.34% to 2.59% among all pollutants, ages, and cycles, with average errors of -0.01% and 0.07% for PTs and LCTs, respectively. In this sensitivity analysis, the PT Regulatory Class 30 fraction was adjusted from the default value of 0.946 to 0.933.

For SHT and LHT, CO_2 and NO_x emission factors have their maximum value at the lowest speed of 5.8 mph, decrease as the speed increases, reaching a minimum value at the speed of approximately 60 mph, and then increase as speed further increases. CO and HC emission rates have their maximum values at the lowest speed of 5.8 mph, and a minimum value at an average speed of 71.7 mph. The differences between MOVES results and simplified model are between -2.24% to 2.31%. The average of the errors among vehicle ages, pollutants and cycles are 0.002% and -0.02% for SHTs and LHTs, respectively.

TABLE IV-6 Comparison of Cycle Average Emission Rates for the Simplified Model versus MOVES for Five Year Old Passenger Cars

Cycle ID	CO_2			NO_X			CO			HC		
	MOVES[a] (g/mile)	Simplified Model[b] (g/mile)	Percent Difference	MOVES (g/mile)	Simplified Model (g/mile)	Percent Difference	MOVES (g/mile)	Simplified Model (g/mile)	Percent Difference	MOVES (g/mile)	Simplified Model (g/mile)	Percent Difference
101	1922	1929	0.35	0.1068	0.1073	0.39	6.58	6.61	0.43	0.0259	0.026	0.36
1033	702	704	0.24	0.0964	0.0967	0.27	2.80	2.81	0.28	0.0159	0.0159	0.26
1043	497	498	0.19	0.0743	0.0745	0.23	2.19	2.19	0.15	0.0105	0.0105	0.23
1041	468	468	-0.06	0.0939	0.0939	-0.03	2.91	2.91	-0.03	0.0141	0.0141	-0.04
1021	417	417	-0.01	0.0649	0.0649	0.02	2.05	2.05	-0.03	0.0091	0.0091	0.02
1026	318	318	-0.06	0.0788	0.0787	-0.05	1.61	1.61	-0.08	0.0094	0.0094	-0.05
1030	397	397	-0.06	0.0887	0.0887	0.02	2.14	2.14	-0.07	0.0118	0.0118	0.02
153	347	346	-0.01	0.0694	0.0694	0.00	1.80	1.80	-0.03	0.0087	0.0087	0.05
1029	351	351	0.06	0.0810	0.0810	0.07	2.11	2.12	0.05	0.0114	0.0114	0.11
1020	318	318	0.03	0.0811	0.0812	0.02	1.53	1.53	0.07	0.0091	0.0091	0.08
1025	306	306	0.09	0.0832	0.0833	0.11	1.57	1.57	0.07	0.0098	0.0098	0.11
1011	312	312	-0.10	0.0846	0.0845	-0.09	1.52	1.52	-0.04	0.0102	0.0101	-0.01
1019	298	297	-0.07	0.0824	0.0823	-0.07	1.46	1.46	-0.01	0.0091	0.0091	0.02
1024	303	303	-0.08	0.0906	0.0905	-0.07	1.69	1.69	-0.04	0.0108	0.0108	-0.03
1018	301	301	-0.01	0.0895	0.0895	-0.01	1.54	1.54	0.02	0.0105	0.0105	0.03

TABLE IV-6 Continued

1017	307	307	-0.05	0.0953	0.0953	-0.03	1.77	1.78	0.02	0.0119	0.0119	0.04
1009	322	322	-0.06	0.113	0.113	-0.11	2.26	2.26	-0.18	0.0165	0.0165	-0.17
158	342	342	-0.05	0.129	0.129	-0.08	3.24	3.24	-0.09	0.0211	0.0211	-0.10
FTP	388	388	na	0.0638	0.0638	na	1.64	1.64	na	0.0082	0.0082	na

[a] MOVES: emission factor estimated using MOVES. For CO_2, the MOVES emission factors are based on cycle average energy consumption and default fuel properties for gasoline.

[b] Cycle average: emission factor calculated using the simplified model based on a Base Emission Rate (BER) and Cycle correction factor (CCF). The BER is estimated using the MOVES model based on the FTP driving cycle. The CCF is given in TABLE 4.

For TBs, CO_2 and NO_x emission factors have maximum values at the lowest speed of 3.1 mph, decrease as the speed increase, reach a minimum value at speed of 60.4 mph and increase as speed increase. CO and HC emission factors have maximum values at the lowest speed of 3.1 mph, and a minimum values at the highest speed of 72.8 mph. The differences between MOVES results and simplified model are between -0.65% and 1.29% for all pollutants, ages, and cycles, and the average error is 0.09%.

Taking into account six vehicle types, four ages, four pollutants, and approximately a dozen or more driving cycles depending on the vehicle type, more than 92% of the prediction errors

of the simplified model are less than 1% compared to the MOVES prediction. Thus, the simplified model is an accurate reduced form version of the more complex MOVES model.

Comparison of Runtime

The key advantage of the simplified model is that it runs much more quickly than MOVES. The processing time is the time from executing a run to obtaining results, during which time there is no user interaction with MOVES. For example, the processing time for the case study for one vehicle type with 18 driving cycles is approximately 10 minutes for MOVES using a 2.93 GHz processor with 8 GB memory, while the processing time is 0.3 seconds using the simplified model in MATLAB for the same number of driving cycles in MATLAB. Thurs, the simplified model is 3,000 times faster than MOVES.

Real World Example

Three real world driving cycles are used with the simplified model to demonstrate application of the model and to illustrate variation in emission rates among cycles with similar average speeds. Theses driving cycles are for non freeway roads with average speeds of approximately 25 mph. All three are based on field measurements conducted in the Raleigh, NC area (*35*). As an example, emission rates are calculated for each cycle for calendar year 2011 zero year old gasoline PCs. The cycle average speed and fraction of time spent in each OpMode is in TABLE 6 and results for cycle average emission rates predicted for four pollutants with each of the MOVES and simplified model are given in TABLE 7.

The differences between MOVES emission factors and model emission rates for these cycles are within $\pm$0.06% among all pollutants. Cycle 1 has the lowest emission rates for all

of the pollutants, and Cycle 3 has the highest. For CO_2 emission rates, the differences among cycles are within $\pm$0.3%. For other pollutants, Cycle 3 has 110% to 260 % higher emission rates than Cycle 1, depending on the pollutant. The higher emission rates for Cycle 3 are associated with a higher fraction of time spent at higher speed and higher VSP. For example, the proportion of time spent at speeds higher than 25 mph with VSP greater than 18 kw/ton is only 4% for Cycle 1 and is over three times greater, at 13%, for Cycle 3. These operation conditions contribute only 12% of the Cycle 1 average emission rate versus 41% for Cycle 3. Cycle 3 also has more acceleration events than Cycle 1. The case study examples illustrate that the simplified model can be used with empirical cycles, will give the same predictions as MOVES, and will produce results that are sensitive to differences in the distribution of OpMode bins even for cycles with similar average speeds.

CONCLUSIONS

The simplified model is designed to efficiently estimate vehicle emissions based on the output of TSMs or TDMs. Many investigators are coupling TDMs or TSMs with emissions models such as MOVES, either by manually transferring data from one model to the other or by attempting to dynamically link the models. In either case, the amount of time required to run the combined models is a significant barrier to conducting case studies. However, it is desirable to couple such models to support estimation of the impact of infrastructure design and traffic control measures on emissions.

Here, a simplified (or reduced form) version of MOVES has been developed and shown to be highly precise in producing the same cycle average emission rates for a wide variety of

vehicle types, vehicle ages, pollutants, and driving cycles. The simplified model takes into account many factors that are constant over a multi-hour traffic simulation based on calibration to a base emission rate obtained via one run of MOVES. Further, the simplified model accounts for variability in cycle average emissions associated with variability in vehicle dynamics based on the same VSP and speed based OpMode bins that are the foundation of MOVES. The simplified model is computationally more simple than MOVES and can easily be encoded as part of a TDM or TSM. For example, the simplified model can be used to estimate emissions for link-based, trip-based, or area-wide driving cycles for simulated vehicles.

There is a minor discrepancy in results from the simplified model versus MOVES when using default regulatory class distributions for PT and LCT, whereas use of default regulatory class distributions for SHT and LHT produced acceptable results. The difference in cycle average emissions results between the simplified and MOVES model was reduced for PT and LCT upon minor adjustments to the regulatory class fraction. However, it has not been possible to yet further diagnose the underlying reason for this apparent discrepancy.

The novelty of this work is that no one else has taken this approach to developing a simplified alternative to the MOVES model that can be incorporated into a TSM or used for iteration case studies such as to evaluate many driving cycles. The simplified version can be executed 3,000 times faster than MOVES itself. The simplified model will be incorporated within a traffic simulation model (TSM) to estimate the impact on emissions of alternative

transportation infrastructure, control strategies, and vehicle mix. Therefore, the simplified model is important for research in transportation and air quality management.

The simplified model demonstrated here takes into account vehicle types that comprise 95% of the onroad fleet. The model can be expanded, if needed, to include other vehicle types. The simplified model is shown to accurately predict differences in cycle average emission rates for cycles with similar average speeds but significant differences in the distribution of engine load. The model is also demonstrated based on applications to empirically observed driving cycles, indicating the flexibility to represent a variety of such cycles. As part of ongoing work, the simplified model developed here will be encoded into a TSM. The combined TSM/emissions model will be applied to case studies to demonstrate methods for evaluating the effect of transportation improvement projects and traffic control measures on project level and area-wide fuel use and emissions.

In the simplified model, there are some "given up" versus MOVES model such as the limited number of pollutants, limited types of vehicle, exhaust emissions only, variations of vehicle fleet among links. Since the purpose is to couple with a TSM, there is no need to include variation of vehicle fleet for different links in the simulated network and pollutants from other process such as cold and hot start are negligible. Also, since the vehicle types covers more than 95% fleet of onroad vehicles, the current model can be a good representative for the vehicle fleet for simulation. However, it would be good to incorporate more pollutants such as particulate matter (PM) and SO_2 into the simplified model because PM and SO_2 are criterial pollutants.

TABLE IV-7 Examples of the Fraction of Time in Each Operating Mode Bin for Real World Driving Cycles

Operating Mode ID	Fraction of Time in Operating Mode Bin by Driving Cycle ID and Cycle Average Speed[a]		
	Cycle 1 (24.7 mph)	Cycle 2 (25.3 mph)	Cycle 3 (25.5 mph)
0	0.142	0.131	0.168
1	0.192	0.265	0.125
11	0.038	0.034	0.068
12	0.079	0.058	0.137
13	0.033	0.007	0.029
14	0.031	0.011	0.016
15	0.014	0.012	0.013
16	0.019	0.015	0.022
21	0.046	0.069	0.055
22	0.029	0.037	0.020
23	0.072	0.075	0.024
24	0.045	0.032	0.024
25	0.051	0.025	0.023
27	0.049	0.059	0.042
28	0.023	0.034	0.033
29	0.004	0.013	0.017
30	0.001	0.007	0.038
33	0.028	0.034	0.053
35	0.078	0.040	0.027
37	0.018	0.024	0.024
38	0.008	0.011	0.018
39	0.002	0.004	0.009
40	0.000	0.005	0.013

[a] Numbers may not add exactly to 1.000 due to rounding.

TABLE IV-8 Comparison of Cycle Average Emission Rates for the Simplified Model versus MOVES for Zero Year old Passenger Cars

Cycle ID	Average Speed (mph)	CO_2			NO_X			CO			HC		
		MOVES[a] (g/mile)	Simplified Model[b] (g/mile)	Percent Difference	MOVES (g/mile)	Simplified Model (g/mile)	Percent Difference	MOVES (g/mile)	Simplified Model (g/mile)	Percent Difference	MOVES (g/mile)	Simplified Model (g/mile)	Percent Difference
1	24.7	402	402	0.041	0.037	0.037	0.052	1.04	1.04	0.052	0.0073	0.0073	0.051
2	25.3	403	403	-0.053	0.049	0.049	-0.014	1.63	1.63	-0.020	0.0108	0.0108	0.010
3	25.5	482	482	-0.007	0.080	0.080	-0.002	3.74	3.74	-0.003	0.0198	0.0198	0.004
FTP	21.4	389	389	na	0.025	0.025	na	0.773	0.773	na	0.0050	0.50	na

[a] MOVES: emission factor estimated using MOVES. For CO_2, the MOVES emission factors are based on cycle average energy consumption and default fuel properties for gasoline.

[b] Cycle average: emission factor calculated using the simplified model based on a Base Emission Rate (BER) and Cycle correction factor (CCF). The BER is estimated using the MOVES model based on the FTP driving cycle.

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PART V **COMPARATIVE ASSESSMENT OF VARIABILITY IN LIGHT DUTY VEHICLE EXHAUST EMISSION RATES BASED ON VEHICLE TYPES, AGE, DRIVING CYCLES, AND AMBIENT CONDITIONS**

ABSTRACT

Light duty gasoline vehicles (LDGVs) , including passenger cars (PCs) and passenger trucks (PTs) comprise more than 70% of the U.S. onroad vehicle fleet. LDGV exhaust emission rates vary with vehicle type, age, driving cycle, and ambient conditions. Although these factors have been evaluated individually, they have not typically been evaluated simultaneously in a consistent framework that also accounts for their interactions. These factors and their interactions are evaluated based on nearly 600 real-world driving cycles measured for 100 LDGVs. These data include PC and PT vehicle types, 1996 to 2013 model years, a variety of road types, and a range of ambient temperature and relative humidity. To deal with the combinatorial challenges of parametric evaluation of these factors, and to enable evaluation of multiple sources of variability simultaneously using a consistent framework, a High Throughput Tool (HTT) was developed, which is a simplified version of the U.S. EPA's MOVES model that runs 1,000 times faster. The HTT is verified and shown to be accurate and precise compared to MOVES predictions. The variability in emission factors between PC and PT, between model year groups that represent different regulatory certification standards, among the real-world cycles, and among a range of ambient conditions are individually and jointly evaluated. CO2 and NOx cycle average emission factors are sensitive to vehicle type, ambient conditions, and driving cycles. NOx emission factors are also sensitive to model year and emission standards. Reductions in NOx emissions for newer versus older vehicles are larger for passenger cars than passenger trucks. Differences in CO2 and NOx emission rates due to temperature are more pronounced for driving cycles with low cycle average speeds. The unique contribution of this work is that

the comparisons are based on a large sample of real-world driving cycles and thus are representative of real world conditions.

INTRODUCTION

Onroad light duty vehicles are a key source of air pollutant emissions, particularly for nitrogen oxides (NOx), carbon monoxide (CO), and hydrocarbons (HC), in the U.S. (U.S. EPA, 2013). Emissions from onroad vehicles are related to vehicle type, vehicle age, vehicle dynamics, and ambient conditions (U.S. EPA, 2009). Although these factors have been quantified individually in previous studies (U.S. DOT, 2013, U.S. EPA, 2013b; Liu and Frey, 2014; Ntziachristos and Samaras,2000; Kousoulidou et al, 2013; Choi and Frey, 2009), there has been comparatively little work to assess inter-cycle variability in emission rates based on real-world cycles and to assess the joint interactive effect of these factors using a consistent framework. Here, multiple sources of variability are compared using a consistent framework. The comparisons are based on a large sample of real-world driving cycles and, thus, are representative of real world conditions

In the U.S., vehicle types are typically defined based on vehicle weight and application. Light duty vehicles (LDVs) comprise more than 70 percent of the onroad fleet in the U.S., and approximately 98 percent or more of these vehicles are gasoline-fueled (U.S. EPA, 2010). LDVs include Passenger Cars (PCs) and Passenger Trucks (PTs). PCs have gross vehicle weight rating (GVWR) $\leqslant$ 2700 kg. PTs, which include minivans, pick-up trucks, and sport utility vehicles (SUVs), have GVWR$\leqslant$ 3900 kg. CO2 emission and fuel consumption rates are related to vehicle type because of variation in weight. PTs tend to be larger, heavier

vehicles than PCs. On average, PT CO2 emission rates are 15 to 50% higher than for PCs (U.S. DOT, 2013, U.S. EPA, 2013).

Vehicle tailpipe exhaust emission standards apply vary over ranges of model years. In the U.S., "Tier 1" emission standards for NOx, CO, and HC were phased in from 1994 to 1996. More stringent "Tier 2" standards were phased in between 2004 and 2006. Compared to Tier 1, Tier 2 standards have emission limits that are 88% and 82% lower for NOx and HC respectively. There is no difference between CO emission limits for Tier 1 and Tier 2. Based on a limited sample of vehicles measured in the real-world, in-use Tier 2 PCs were found to have 96 percent lower NOx emission rates and 80 percent lower CO emission rates than Tier 1 PCs, with little change in HC emission rates (Liu and Frey, 2014). However, the HC emission rates were generally low for both groups of vehicles. A Tier 3 standard is scheduled to be phased in from 2017 to 2025 (U.S. EPA, 2014). While the Tier 3 standard is predicted to lead to further reductions in tailpipe exhaust emissions, it is not yet possible to assess the effectiveness of the standard based on in-use data.

On an annual basis, vehicle manufacturers are subject to "corporate" or "fleet" fuel economy standards in the U.S. However, the fuel economy of individual vehicle models within the fleet sold by a manufacturer are not regulated. Fleet fuel economy standards from the 1990 to 2013 model years varied from 27 miles per gallon (mpg) to 34 mpg for PCs and 20 mpg to 26 mpg for PTs (U.S. DOT, 2014). The production weighted fuel economy for PCs has typically included a range of 20 mpg to 30 mph for the last two decades, whereas the production weighted fuel economy for passenger trucks has typically included a range of 15

mph to 22 mpg over the same time period (U.S. EPA, 2013). The median corporate average fuel economy of both PCs and PTs was relatively constant from approximately 1985 to 2005, but in recent years there is evidence of some increase. Beginning in 2017, the U.S. will implement new fuel economy and greenhouse gas emission standards for PCs and PTs, to be phased in through 2025 (U.S. DOT, 2012).

Driving cycles affect cycle average CO2, NOx, CO and HC emission rates. For example, the CO2 emission rate in grams per mile is comparatively high for cycles with low average speed and comparatively low for cycles with average speeds of 50 mph to 60 mph (Ntziachristos and Samaras,2000; Kousoulidou et al, 2013). However, for a given cycle average speed, emission rates are higher if there is transient variability in speed versus driving at constant speed (Choi and Frey, 2009). The effect of variability in emission rate versus cycle average speed is typically assessed based on standard chassis dynamometer driving cycles, but has not been adequately assessed based on a large sample of observed real world cycles. Because emission rates and fuel economy vary with respect to driving cycles, comparisons of emission rates and fuel economy are needed with respect to variation in driving cycles. This is an example of an interaction effect between model year, vehicle age, and driving cycle.

Vehicle emission rates of some pollutants are sensitive to ambient conditions, including ambient temperature and relative humidity. The U.S. EPA has developed various correction factors to adjust emission factors for a base ambient condition to other ambient conditions (U.S. EPA, 2010). Ambient conditions affect occupant demand for air conditioning, which affects engine load and emission rates (U.S. EPA, 2010). The effect of increased engine

power demand at a given temperature is to increase emission rates of pollutants such as CO, HC, and NOx. Very low ambient temperatures, such as 20 oF, are known to be associated with higher engine-out emissions of products of incomplete combustion such as CO and HC (Austin, et al, 1983; Opat, et al, 2007). Lower intake air temperatures lead to lower peak cylinder temperature and, hence, lower rates of oxidation of intermediate products of combustion (Flagan and Seinfeld, 1988). Higher ambient temperatures, such as 95 oF, are associated with an increase in NOx emission rates (U.S. DOT, 2002). NOx formation is sensitive to peak temperatures in the cylinder, which increase with increasing intake air temperature (Flagan and Seinfeld, 1988). In contrast, increased humidity tends to suppress NOx formation, since moisture is a thermal diluent that tends to lower peak flame temperature (U.S. EPA, 1999).

However, there are many limitations of previous evaluation of factors that affect emissions. For example, a comparison of CO2 emission rates between PCs and PTs based on national wide fleet average data did not take into account variability related to vehicle age, driving cycles, or ambient conditions (U.S. DOT, 2013, U.S. EPA, 2013). A recent evaluation of the effect of model years on emission rates for PCs did not consider vehicle type and ambient conditions (Liu and Frey, 2014). Evaluations of variability in emission rates related to driving cycles have not taken ambient conditions into account (Ntziachristos and Samaras, 2000; Kousoulidou et al, 2013). Evaluation of the effect of ambient conditions have not systematically taken into account variability in driving cycles (U.S. EPA, 2011). Furthermore, even when multiple sources of variability have been evaluated, the interactive effect of two or more sources of variability is typically not quantified. For example,

variability in emission rates results from the joint effect of variability in multiple factors simultaneously, such as vehicle type, age, driving cycles, and ambient conditions. Therefore, evaluation of the interactive impact of the factors on running exhaust emissions is needed.

In the U.S., onroad vehicle emission rates are typically estimated using the U.S. EPA's Motor Vehicle Emission Simulator (MOVES). Tailpipe exhaust emission rates are estimated in MOVES based on operating mode (OpMode) bins that differ with respect to engine power demand, taking into account braking, idle, and three speed ranges (U.S. EPA, 2009). The OpMode bins are time-weighted to represent any user-supplied driving cycle. Cycle average emission rates can be estimated for selected vehicle types, such as PC and PT, selected calendar years and vehicle ages (which translates to model year), and user-specified ambient conditions. Cycle average emission factors are corrected based on temperature and humidity. Therefore, MOVES accounts for the key factors identified here. However, to date, there has not been an evaluation of the interactive effect of these factors taking into account a large sample of real-world driving cycles.

The research questions here are: (1) How sensitive are cycle average emission factors to variations in vehicle type, age, driving cycle and ambient conditions for real world driving cycles?; and (2) What are the interactions between these sources of variability?

METHODS

The variability of emission factors for selected factors, and interactions between these factors, are evaluated based on real-world driving cycles for selected vehicle types, age groups, and ambient conditions.

Specification of Scenarios

Key sources of variability in emission factors were identified as the focus for systematic analysis and comparison here. These factors include vehicle type, vehicle age, ambient conditions, and driving cycles. In the U.S., PCs and PTs comprise more than 80% of onroad vehicles (U.S. EPA, 2010) and thus are the focus here. Light duty vehicles in the U.S. are predominantly gasoline-fueled.

Vehicle age is related to model year, which in turn is related to emissions certification standards and emission control techniques. Model years subject to Tier 1 and Tier 2 standards are compared for both PCs and PTs.

To evaluate the impact of ambient conditions, three ambient scenarios are evaluated. These scenarios include the ambient conditions used as a reference case in the EPA MOVES model and two other cases that represent variability in ambient conditions in the Raleigh, NC area where driving cycles were measured. Furthermore, the focus here is on higher temperatures. The most prevalent air quality problem in the U.S. is non-attainment of the National Ambient Air Quality Standard for ozone, for which emissions of both nitrogen oxides and organic compounds are precursors. The highest ozone levels occur during warmer months (EPA, 2013). Thus, the ambient conditions evaluated include: (1) base case conditions assumed in MOVES of 75 ^{o}F and 58% relative humidity; (2) a lower temperature and humidity case of 65 ^{o}F and 37% relative humidity, respectively; and (3) a summer case of 95 ^{o}F and 80% relative humidity.

The complete set of scenarios are shown in Table 1. In addition to 12 scenarios based on combinations of 2 vehicle types, 2 age groups, and 3 ambient conditions, there is a 13th scenario that is based on the observed variation in vehicle type, age group, and ambient conditions for a measured onroad fleet of 100 vehicles.

Empirical Data

Empirical driving cycle data were measured for 66 PCs and 34 PTs. The measured vehicles include 1996 to 2013 model years, and thus include both Tier 1 and Tier 2 vehicles, and were 0 to 14 years old at the time of the measurement. Measurements were conducted from calendar years 2008 to 2013 .

Variability in vehicle emission rates within a driving cycle are influenced by engine power demand, which can be estimated based on Vehicle Specific Power (VSP) (Jimenez-Palacios, 1999). VSP is a function of speed, acceleration, and grade and takes into account changes in kinetic and potential energy of the vehicle, rolling resistance, and aerodynamic drag. Fuel use is approximately a linear function of positive VSP and is approximately constant over a range of negative VSP. Vehicle emission rates are typically a monotonic function of positive VSP. For each measured vehicle, an On-Board Diagnostic (OBD) scantool was used to record vehicle speed and Global Position System (GPS) receivers with barometric altimeters were used to record position and changes in altitude. The OBD reported speed was interpolated to a 1 Hz basis. Acceleration was inferred based on differences in speed from one second to the next. Road grade was inferred based on statistical analysis of changes in altitude measured with barometric altimeters and the corresponding change in position

observed based on GPS (Yazdani and Frey, 2014). Previously developed quality assurance procedures were used to check and process the measured data (Sandhu and Frey, 2013).

Each vehicle was measured on four routes developed in a prior study by Frey et al. (2008). The routes are based on alternative paths between two origin/destination (O/D) pairs. Routes A and C are paths between NC State University, which is near the downtown central business district in Raleigh, to a residential area in north Raleigh. Routes 1 and 3 are paths between north Raleigh and Research Triangle Park, which is a business park. Thus, the selected routes represent typical commuting patterns in the local area. For each O/D pair, alternative routes were selected that have different mixes of road type with respect to time and distance. Routes A and 3 are comprised entirely of arterial roads, whereas Routes C and 1 include freeways. To isolate the effect of freeway driving from driving on arterials, the measured driving cycles for Routes C and 1 were divided into freeway and nonfreeway segments. Thus, a total of six cycles (A, C nonfreeway, C freeway, 1 nonfreeway, 1 freeway, and 3) were analyzed for each measured vehicle. The total distance traveled by each vehicle is approximately 110 miles. For 97 of the measured vehicles, complete data were obtained on all six of the driving cycles. For three vehicles, data were available for only 3 of the 6 cycles. Thus, valid measurements were obtained on 591 driving cycles. The cycle average speeds range from 10 mph

In recent work, data from these 591 driving cycles were analyzed to evaluate whether there are significant differences in the distribution of vehicle speed and acceleration (Liu and Frey, 2015). The results demonstrate that each vehicle is capable of operating under the ranges of

speed and acceleration of any of the observed driving cycles. Thus, for purposes of analysis, cycle average emission rates can be estimated for any of the measured vehicles based on any of the measured driving cycles.

Emission Factors

The methodological approach to emission factor estimation in MOVES is used here. MOVES OpModes are defined based on three ranges of vehicle speed and, within each speed range, based on ranges of VSP (U.S. EPA, 2009). For PCs and PTs, there are 23 OpMode including braking, idling, 6 modes for speeds ranging up to 25 mph, 9 modes for speeds ranging from 25 mph to 50 mph, and 6 modes for speeds over 50 mph. MOVES includes default OpMode emission rates based on vehicle type, regulatory class, and age (U.S. EPA, 2009). MOVES includes algorithms for adjusting emission rates based on ambient temperature and humidity (U.S. EPA, 2010). The methodological approach used here for estimation of cycle average emission factors is based on the approach used in MOVES.

High Throughput Emission Factor Estimation

MOVES is an computationally intensive model. For one vehicle type, vehicle age, set of ambient conditions, and driving cycle, it takes about one minute to estimate cycle average emission rates for four selected pollutants. Thus, to estimate emission factors for 591 driving cycles for 13 scenarios, it would take about 130 hours of run-time. To reduce run time, a high throughput tool (HTT) was previously developed to enable faster assessment of factors that lead to variations in cycle average emission rates and to enable rapid comparisons between vehicle types, cycles, and ambient conditions (Frey and Liu, 2013). The HTT

estimates cycle average emission factors based on a base emission rate and a cycle correction factor. The base emission rate is calibrated using one MOVES run. The cycle correction factor enables estimation of cycle average emission rates for any user-specified, including real-world, driving cycle based on adjustment from the base emission rate taking into account differences in the distribution of engine power demand, speed, braking, and idling between the specified and base cycle. The fleet average cycle average emission rate for a pollutant for a user-specified driving cycle is given by:

$$CE_{p,c} = \sum_v \left\{ \left[\sum_a (EF_{p,b,a,v} \times CCF_{p,c,a,v} \times f_{a,v}) \right] \times f_v \right\} \quad (1)$$

Where,

$CE_{p,c,}$ = cycle average emission factor for any arbitrary driving cycle c, for pollutant p, for a fleet of vehicles with mixed types and ages, gram/mi

$ER_{p,b,a,v}$ = base emission rate for base cycle b, age a, vehicle type v, and pollutant p, gram/mi

$CCF_{p,c,a,v}$ = cycle correction factor for driving cycle c, age a, vehicle type v, and pollutant p

$f_{a,v}$ = age fraction for age a and vehicle type v

f_v = vehicle type fraction for vehicle type v

c = cycle c

b = base cycle

p = pollutant

The Cycle Correction Factor (CCF) for a given pollutant, cycle, vehicle type, and vehicle age is the ratio of the emission rate for any cycle to that of the base cycle.

$$\mathrm{CCF}_{p,c,a,v} = \left(\frac{\left(\sum_m f_m^c \times \mathrm{ER}_{p,a,v,m}\right)}{\left(\sum_m f_m^b \times \mathrm{ER}_{p,a,v,m}\right)} \right) \left(\frac{V^b}{V^c} \right) \tag{2}$$

Where,

$\mathrm{ER}_{p,a,v,m}$ = default emission rate for pollutant p, age a, vehicle type v, in operating mode bin m, gram/hour

$f_m{}^c$ = fraction of time in OpMode bin m in cycle c

$f_m{}^b$ = fraction of time in OpMode bin m for base cycle b

V^c = cycle average speed for cycle c, mph

V^b = cycle average speed for base cycle b, mph

The previous version of the HTT was designed to quantify vehicle cycle average emissions of PCs and PTs for zero to 30 years old. To verify the HTT, emission factors were estimated using both the HTT and MOVES for PCs and PTs for 18 MOVES default driving cycles, ranging in average speed from 2.5 mph to 76 mph, and for MOVES base case ambient conditions. The relative difference between HTT's results and MOVES estimates are within ±5% for each vehicle type, age, driving cycle, and pollutant (Frey and Liu, 2013). Thus, the HTT was deemed to be an accurate and sufficiently precise simplified version of MOVES

that enables more rapid emission factor estimation over a range of vehicle types, ages, and driving cycles.

The previous version of the HTT did not include adjustments for differences in ambient conditions compared to the MOVES base case. Here, the HTT is updated such that cycle average emission factors are multiplied by correction factors for humidity and ambient temperature using the same method as MOVES. The HTT runs 1,000 times faster than MOVES.

MOVES includes a humidity correction for NO_x tailpipe exhaust emissions (U.S.EPA, 2010b). The correction method is based on estimation of specific humidity, $H_{specific}$, which is the mass of water vapor per mass of dry air, based on the observed relative humidity, ambient pressure, and dry bulb temperature. EPA estimates specific humidity in archaic units of grains of water vapor per pound of dry air. Based on $H_{specific}$, a humidity correction factor is estimated:

$$K = 1.0 - [(BH_s - 75.0) * C_h]$$

(3)

Where,

K = humidity correction factor (dimensionless);

BH_s = bounded specific humidity, grains of water per pound of dry air. $BH_s = 21$ if $H_{specific} < 21$ grains/lb. $BH_s = 124$ if $H_{specific} > 124$ grains/lb. Otherwise, $BH_s = H_{specific}$;

C_h = humidity correction coefficient, 0.0038 for gasoline vehicles and 0.0026 for diesel vehicles

K typically ranges from 0.8 to 1.2. The value of K is based on ambient temperature, relative humidity, and barometric pressure, but is not sensitive to driving cycles, vehicle type, or age.

Cycle average emission rates for CO_2, NO_x, CO, and HC are adjusted in MOVES based on ambient temperature (U.S. EPA, 2010). The temperature correction takes into account the typical frequency of air conditioning (AC) use under conditions of high ambient temperature and relative humidity, taking into account the fraction of vehicles with AC and that the fraction of vehicles with operational AC decreases with age. The temperature correction varies with OpMode bin.

The updated HTT including both humidity and temperature corrections was verified by comparing its results with emission factors estimated based on MOVES for the same vehicle type, age, ambient conditions, and driving cycles. The verification was based on PC and PT vehicle types, examples of Tier 1 and Tier 2 vehicles based on vehicles of ages zero and 10 years old, and 18 default driving cycles that are used in the MOVES model.

Verification of the temperature and humidity adjustments incorporated into the HTT focused on typical summer ambient conditions, since the air quality management problems most affected by vehicle emissions, particularly NO_x and HC, in the U.S. are related to tropospheric ozone formation. The selection of ambient conditions takes into account the reference conditions used in the MOVES model and higher temperatures that would be

expected to lead to higher ozone production. Thus, the ambient conditions include a base case (75 ^{o}F with relative humidity of 58%), average temperature and humidity for summer (85 ^{o}F with relative humidity of 58%), and hot and humid day for summer (95 ^{o}F with relative humidity of 80%).

Sensitivity Analysis of the Emission Factors of Empirical Conditions

Standardized Rank Regression Coefficients (SRRCs) are used to assess the relative contribution of each of several simultaneously varying factors with respect to variability in cycle average emission rates among all observed driving cycles for four vehicle groups, including Tier 1 and Tier 2 for each of PCs and PTs. SRRC is appropriate for comparative evaluation of multiple factors that have different dimensions (or scales) (Hamby, 1995). SRRCs are based on regression analysis of the rank values of each explanatory variable and the dependent variable (i.e. cycle average emission rate). Rank values are inferred by ordering *n* sample data from smallest to largest, and assigned a rank of 1 to the smallest value through a rank of n to the largest value. Thus, rank regression provides insight regarding the monotonicity of the relationship between a dependent variable and each explanatory variable. Based on prior knowledge, cycle average emission rates are expected to be sensitive to temperature, humidity, age, and dynamic characteristics of the driving cycles (U.S. DOT, 2013, U.S. EPA, 2013b; Liu and Frey, 2014; Ntziachristos and Samaras,2000; Kousoulidou et al, 2013; Choi and Frey, 2009). Although driving cycles are often summarized in terms of cycle average speed, cycle average emission rates are known to be affected by transient operation that is related to changes in speed or changes in acceleration. Therefore, the SRRC

analysis is based on the hypothesis that cycle average emission rates for a given vehicle group and pollutants vary depending on temperature, humidity, age, cycle average speed, standard deviation of speed, average acceleration, and standard deviation of acceleration:

$$R_{EF} = \sum a_i \left(\frac{R_i - \overline{R}_i}{S_{R_i}} \right) \tag{3}$$

R_{EF} = rank of dependent variable, emission factor, g/mi

a_i = standardized regression coefficient

R_i = rank of input variables, i=1, 2, 3, 4, 5, 6 for cycle average speed, standard deviation of

speed, average acceleration, standard deviation of acceleration, temperature, and humidity, respectively

$\overline{R}_i$ = mean of the rank of the input variable

S_{R_i} = standard deviation of the rank of the input variable

The relative magnitude of the SRRCs among the explanatory variables indicates the relative strength of the monotonic relationship between the dependent variable and the explanatory variable. SRRCs with larger magnitudes, whether positive or negative, imply stronger sensitivity of cycle average emission rate to the particular explanatory variable. SRRCs that are not statistically different from zero imply that there is not a monotonic relationship..

RESULTS

The HTT was validated based on comparison to the MOVES model. The verified HTT was used to estimate cycle average emission rates for over 7,683 emission factors per pollutant, for a total of nearly 15,400 emission factors, accounting for 591 real-world driving cycles for each of 13 scenarios, as defined in Table 1. Based on these scenarios, the sensitivity of the emission factors to vehicle type, vehicle age, driving cycles, and ambient conditions was evaluated.

Verification of High Throughput Tool

To illustrate the sensitivity of cycle average NO_x emission factors to humidity, the variation in K is illustrated in Figure 1 for humidity from 0 to 100% for three selected temperatures. At temperatures of 65 ^oF and 75 ^oF, K decreases as relative humidity increases. This trend is consistent with findings in EPA (1999), because humidity is a thermal diluent that leads to reduced NO_x emissions. At a temperature of 95 ^oF, K decreases as relative humidity increases from 10% to 50%, and stays relatively constant from 50% to 100% because MOVES is using a bounded specific humidity to calculate K. At 95 ^oF, specific humidity is larger than 124 grains of water per pound of dry air for relative humidity greater than 50%. However, the bounded specific humidity does not exceed 124 grains of water per pound of dry air. At very low relative humidity of 10 percent or less, there is no difference in the K value over the range of temperatures considered. At higher relative humidity, the K value tends to lower for higher temperature because given the same relative humidity, the specific humidity is higher for higher temperature, and therefore the thermal diluent effect of NO_2 is stronger.

The accuracy with which the humidity and temperature correction algorithms were incorporated into the HTT was verified based on comparison to MOVES for selected ambient conditions. The cycle average emission factors estimated using the HTT were compared with MOVES estimates over a range of ambient conditions. For CO_2, errors in cycle average emission rates range from -8% to 8% with an average of -1%. For NO_x, errors range from -12% to 9% with an average of -3%. More than 70% of the errors are within -5% to 5%. Therefore, the HTT with ambient correction is deemed to be accurate for estimating cycle average emission factors.

Cycle Average Emission Factors

Cycle average emission factors for 591 empirical driving cycles were estimated using the HTT for each of 13 case studies. The overall average of the 591 emission factors and the 95 percent confidence of the overall average are given for each case study in Table 1 for CO_2 and NO_x.

CO_2 and NO_x cycle average emission rates are both sensitive to vehicle types. Figure 2 shows variability in cycle average CO_2 and NO_x emission factors versus cycle average speed for Tier 1 PCs and PTs under base case ambient conditions. For PCs, CO_2 emission factors are high at low cycle average speed and reach a minimum value around 50 mph. The average of the 591 Tier 1 PC CO_2 emission factors at 75 ^{o}F over all cycle average speeds is 385 g/mi. The highest PC emission factors at low cycle average speeds, such as in the range of 10 mph to 20 mph, are up to 60% higher than the emission factors in the speed range of 50 mph to 60

mph. The trend is qualitatively similar for PTs. The average of 591 Tier 1 PT CO_2 emission factors at 75 ^{o}F is 547 g/mi, which is 42 percent higher than for PCs.

The higher cycle average CO_2 emission rates for PTs compared to PCs, which correspond to higher fuel consumption and lower fuel economy, are because of differences in engine displacement and vehicle weight. The average engine displacement and vehicle weight used in the MOVES default emission rates is not reported by EPA. However, as an example, the average engine displacement for the 66 PCs for which real-world driving cycles were measured was 2.4 L, and for the 34 PTs was 3.9 L. Thus, on average, the PTs are expected to have much larger engines than the PCs. The average gross vehicle weight rating was 1400 kg for the PCs and 1900 kg for PTs. Thus, the average PT engine had approximately 60% more displacement and the average PT had approximately 36 percent more weight than the PCs. The comparison between CO2 emission rates is approximately similar to the comparison between average vehicle weight. The sensitivity of CO_2 emission rate versus vehicle type and weight is qualitatively consistent with findings of U.S. DOT (2013) and U.S. EPA, (2013).

There is no significant difference in cycle average CO_2 emission rates between Tier 1 and Tier 2 PCs, nor between Tier 1 and Tier 2 PTs. The lack of significant change in CO_2 emission rates from Tier 1 to Tier 2 is related to the lack of change of fuel economy for each vehicle type over the same time period.

Similar to the trend in CO_2 emission rates versus cycle average speed, NO_x emission factors at low speeds between 10 mph to 20 mph are 40% higher than those at speeds of 50 mph to

60 mph for Tier 1 PCs. Averaged over all 591 real-world cycles, the average of the cycle average NO_x emission factors for Tier 1 PTs are approximately 2.4 times higher than those of Tier 1 PCs. For Tier 2 PTs, the average cycle average NO_x emission rates are approximately 4 times higher than for Tier 2 PCs. Whereas the PT cycle average NO_x emission rates tend to increase from 50 mph to 70 mph, the cycle average emission rates for PCs are approximately constant over the same speed range. The state of Texas has identified the lack of sensitivity of cycle average NO_x emissions as a justification for reversal of "environmental speed limits" (NCTCOG, 2014). For example, the speed limit has been raised from an "environmental speed limit" of 70 mph to 85 mph on a toll road between San Antonio and Dallas. However, as shown in Figure 1(a), CO_2 emission rates tend to increase with cycle average speed at higher speed, and in Figure 1(b) the trend in NO_x emission rate is different for PTs versus PCs. Thus, attempting to generalize the trends in emission rates of one pollutant for one type of vehicle to all pollutants from all vehicle types that operate on a particular road may produce misleading inferences.

Tier 2 PCs have 90% lower cycle average NO_x emission rates than Tier 1 PCs, as indicated in Figure 3. For PTs, the cycle average NO_x emission rates for Tier 2 are 84% lower than for Tier 1. The reduction in NO_x is consistent with findings in Liu and Frey (2014) and He *et al*. (2009). The relative reduction is approximately comparable to the reduction in emission limits when comparing the two standards. The percent reduction is approximately the same over the range of ambient conditions evaluated here. However, the trend in cycle average NO_x emission rates at high speeds is not the same for Tier 2 versus Tier 1 PCs. The cycle

average NO_x emission rates for Tier 2 PCs, although lower, are more sensitive than those of Tier 1 PCs to increases in cycle average speed for speeds greater than 60 mph.

Furthermore, the results in Figures 2 and 3 illustrate that cycle average speed alone does not fully explain the trend in cycle average emission rates. For example, at a cycle average speed of 20 mph, Tier 1 PT cycle average NO_x emission rates vary from 1.0 g/mi to 1.6 g/mi (or by 60%), because of differences in the distribution of engine power demand from one cycle to another. Tier 2 PC cycle average NO_x emission rates vary by more than 100% at a cycle average speed of 20 mph. Thus, the manner in which the vehicle is driven, and not just the speed, is an important determinant of cycle average emission rate.

The sensitivity of average emission rates versus speed ranges and ambient temperature are illustrated in Figure 4. To enable quantification of the relative difference in cycle average emission rates between ambient conditions, cycle average CO_2 and NO_x emission factors for 591 driving cycles are averaged for every 10 mph range of cycle average speed for each set of ambient conditions for the example of Tier 1 PCs. Each data point is the average of emission factors with cycle average speeds within the speed range. The number of driving cycles in each speed range varies from 10 (for speeds >70 mph) to 250 (for the 20 mph to 30 mph speed range). For a given temperature, CO_2 emission factors are relatively high in the 10 mph to 20 mph low speed range, and decrease as cycle average speed increases to approximately the 50 mph to 60 mph range, similar to the finding based on Figure 2(a). The cycle average CO_2 emission rates for all temperatures tend to increase at high speed, such as when comparing the >70 mph speed range to the 50 mph to 60 mph speed range.

CO_2 cycle average emission rates are sensitive to ambient temperature at all speed ranges. The lowest CO_2 emission rates among the three temperatures considered are at 65 ^oF, for which there is little use of air conditioning. In contrast, the highest CO_2 emission rates, which also indicate higher fuel consumption, are at the 95 ^oF temperature, for which there is extensive use of air conditioning. The relative variation in CO_2 cycle average emission rates is more pronounced at low cycle average speeds, for which the difference averages 30% for 95 ^oF versus 65 ^oF at cycle average speeds of 10 mph to 20 mph. At cycle average speeds of 50 mph to 60 mph, the average difference is only 18%. On average over all 591 driving cycles, the cycle average CO_2 emission rates at 95 ^oF are approximately 25 percent higher than at 65 ^oF. The cycle average emission factors are more sensitive to specific driving cycles in low speed ranges, because driving cycles at lower speed range has more variability in accelerations and stops, while driving cycles at higher speed range have a tendency to be more constant speed with less variations. In the lower speed range, there is a greater fraction of time spent in idling and in low engine power demand modes. The relative effect of air conditioner use on fuel use and CO_2 emissions is more pronounced under low versus higher engine power demand. Therefore, the relative difference in low speed ranges is greater than for high speed ranges.

Tier 1 PC NO_x cycle average emission factors are sensitive to ambient temperature for low cycle average speeds, but are insensitive to ambient temperature for cycle average speeds of approximately 50 mph or higher. For example, for cycle average speeds of 10 mph to 20 mph, the cycle average NO_x emission rates at 95 ^oF are approximately 60% higher than those at 75 ^oF. At these low speeds, the increase in NO_x emission factors from low to high

temperature is the next effect from an increase air conditioning usage, which doubles the NO_x emission rate, partially compensated by an increase in specific humidity, which tends to decrease NO_x emission rate by approximately 20%. At higher speed, such as in the 60 mph to 70 mph speed range, there is no net difference in NO_x emission rate, which is the result of an increase for more air conditioning use and a compensating decrease related to higher specific humidity. The effect of air conditioning on NO_x emission rate is less pronounced for the higher speed cycles because the incremental increase in engine load is smaller relative to the cycle average engine power demand.

CO_2 emission factors increase as temperature increases for both PCs and PTs and for both Tier 1 and Tier 2 vehicles of each vehicle type. On average over all cycle average speeds and the four vehicle groups, CO_2 emission factors are about 8% higher for the 75 ^oF case than for the 65 ^oF case and they are about 25% higher for the 95 ^oF case versus 65 ^oF case. The relative difference is larger for the low speed range than for the high speed range. This is because the incremental engine load for air conditioning is a smaller proportion of total engine load for higher speed cycles that have higher average engine power demand.

Among all four vehicle groups, NO_x emission factors increase with temperature for cycle average speeds from 10 mph to 50 mph. On average of 591 driving cycles, the cycle average NO_x emission factors at 75 ^oF for each vehicle group are 20% higher than that of the 65 ^oF case. Overall of all driving cycles average NO_x emission factors at 95 ^oF are about 55% higher than at 65 ^oF for Tier 1 and Tier 2 PCs and PTs. Similar to Tier 1 PCs, the relative

increase in CO_2 emission rate with higher temperature tends to decrease for the other three vehicle groups with increasing cycle average speed.

Based on the mean and 95% confidence in interval on the mean for the case study scenarios based on vehicle type, tier, and ambient condition, as given in Table 1, there is no significant difference in average CO_2 emission rate between Tier 2 versus Tier 1 PCs. However, the Tier 2 NOx emission rates are significantly lower than for Tier 1 by approximately 91 percent over all ambient conditions considered. However, for PTs, the Tier 2 cycle average CO_2 emission rates are approximately 16 percent lower than for Tier 1 PTs. In MOVES, the PT emission rates are averaged from three PT weight ranges. The proportion of heavier PTs is larger for Tier 1 vesus Tier 2 PTs. The difference in weight distribution of PTs is in part a response to more stringent fuel economy standards in recent years. The Tier 2 PTs have cycle average NO_x emission rates approximately 84 percent lower than for Tier 1, averaged over the three selected ambient conditions. While Tier 1 PTs have CO_2 emission rates that average 43 percent higher than Tier 1 PCs, over all evaluated ambient conditions, Tier 2 PTs have CO_2 emission rates that are only 20 percent higher, on average, than Tier 1 PCs. However, PTs have comparatively much higher NOx emission rates than PCs for newer versus older vehicles. Tier 2 PTs have NOx emission rates approximately 4 to 4.5 times higher than for Tier 2 PCs, whereas Tier 1 PTs had NOx emission rates averaging only 2.3 to 2.4 times higher than for Tier 1 PCs. Thus, whereas the differences in average CO_2 emission rates appears to be decreasing between PTs versus PCs, the relative difference in NOx emission rates is increasing.

The empirical case study in Table 1 is based on averaging of all four vehicle groups and among observed ambient conditions from field measurements. Based on the proportion of Tier 1 PCs, Tier 2 PCs, Tier 1 PTs, and Tier 2 PTs for which real world driving cycles were measured, and the temperature and humidity observed for each driving cycle, the overall cycle average CO_2 emission rate is 428 g/mile (±10 g/mile) and the overall cycle average NO_x emission rates is 0.38 g/mile (±0.04 g/mile). Based on data in Table 1, if the same proportion of vehicles of each group all operated at the 65 ^oF and 37% RH condition, the overall average emission rates would be 390 g/mile for CO_2 and 0.28 g/mile for NO_x. In contrast, if the same proportion of vehicles in each group operated at 95 ^oF and 80% RH, the overall average emission rates would be 487 g/mile for CO_2 and 0.43 g/mile for NO_x, which is an increase of 25% and 57% compared to the lower temperature case, respectively. However, the overall range in variability for the average CO_2 emission rates is 78 percent, from 357 g CO_2/mile for Tier PCs at 65 ^oF, to 636 g CO_2/mile, for Tier 1 PTs at 95 ^oF. Thus, for CO_2, the variability related to vehicle type is much larger than that for ambient conditions. For NO_x, the average emission rates vary by a factor of over 40, from 0.04 g NO_x/mile for Tier 2 PCs at 65 ^oF, to 1.68 g NO_x/mile for Tier 1 PTs at 95 ^oF. Thus, there is more variability among vehicle groups than between ambient conditions with respect to cycle average NO_x emission rates.

The inter-cycle variability for a given case study is similar or greater than the differences in average values when comparing case studies. For example, for Tier 1 PTs at 75 ^oF, the CO_2 cycle average emission rates vary from 294 g/mile to 611 g/mile among the 591 driving cycles. The maximum value is 108 percent larger than the minimum value. For NO_x, the

maximum cycle average of 0.93 g/mile is 144 percent larger than the minimum cycle average of 0.38 g/mile. On average over all 12 of the case study scenarios for specific vehicle types, tiers, and ambient conditions, the inter-cycle variability from minimum to maximum is approximately 108 percent for CO_2 and 233 percent of NO_x. Thus, inter-cycle variability is also a substantial source of variability in cycle average emission rates.

The results of an integrated analysis of the effect of ambient conditions and driving cycle characteristics on variability in cycle average emission rates for each of the four vehicle groups is given in Table 2, based on SRRCs. Since the cycle average emission rates for each pollutant and vehicle group tend to reach a minimum around 50 mph to 60 mph, the data were stratified. For each vehicle group, the analysis is done separately for cycle average speeds <50 mph and for cycle average speeds ≥50 mph.

For Tier 1 PCs at speed<50 mph, CO_2 emission factors are positively related to temperature, standard deviation of speed, standard deviation of acceleration, and negatively (or inversely) related to average speed. Cycle average speed is the most sensitive predictor of CO_2 cycle average emission rates, with the largest magnitude SRRC. Temperature and standard deviation of acceleration are the second most important predictors and are of approximately similar sensitivity, with SRRCs of similar magnitude (7.1 and 8.5). The standard deviation of speed is a sensitive but weak predictor, with a relatively low magnitude SRRC. This result implies that cycle average CO_2 emission rates depends on the driving cycle, including average speed, standard deviation of acceleration, and standard deviation of speed, and on ambient temperature. As cycle average speed increases up to 50 mph, the CO_2 emission rate

tends to decrease. The CO_2 emission rate tends to increase with temperature, with more variability in speed, and with more variability in acceleration. The very high R_2 of the rank regression model implies that the SRRCs explain most of the variability in the cycle average emission rates. For speed ≥50 mph, the cycle average CO_2 emission rate is more sensitive to variability in speed than it is to either cycle average speed or ambient temperature.

For Tier 1 PCs at speed <50 mph, the cycle average emission rates are mostly sensitive to temperature, but the coefficient of determination of the fitted rank regression model is very low at only 0.07. Therefore, although ambient temperature is statistically significant in this model, it is not a strong predictor of the inter-cycle variability in NOx emission rates. At high speed ≥50 mph, none of the selected variability offer any significant explanatory power for variability in cycle average emission rates. Of course, the emission rates are sensitive to differences in time spent in each of the OpMode bins.

Among the four vehicle groups, the low speed CO_2 rank regression models are statistically significant with coefficients of determination ranging from 0.52 to 0.90. Cycle average speed is a significant factor for all four vehicle groups. For PCs, variation in speed and acceleration are also significant factors, but for PTs these factors are not significant. Ambient temperature is a significant factor for all vehicle groups, but relative humidity is significant only for Tier 2 PTs. Overall, the CO_2 emission rate inter-cycle variability at low speed appears to be most sensitive to driving cycle characteristics for all four vehicle groups. At high speed the inter-cycle variability in CO2 emission rates is sensitive to driving cycle

characteristics for three of the four vehicle groups, with the exception of Tier 2 PTs, and is sensitive to ambient temperature with the exception of Tier 2 PCs.

For NO_x emission rates, there is little to no statistically significant monotonic relationship with indicators of driving cycle characteristics of ambient temperature, except for Tier 1 PCs at low speeds with respect to temperature. For PTs, the cycle average NOx emission rates have statistically significant monotonic relationships with driving cycle characteristics for Tier 1 and with both driving cycle and ambient characteristics for Tier 2, but the relationships are weaker or not significant at higher speeds.

The effect of vehicle type, age, ambient conditions and driving cycles on variation in CO_2 and NO_x cycle average emissions rates are compared. For CO_2, variation among driving cycles leads to variability of 108% when comparing the largest to smallest cycle average emission rate for a given vehicle group and ambient condition. PTs have CO_2 emission rates that are as much as 42 percent higher than PCs. The CO_2 emission rates vary by about 25 percent among the selected ambient conditions. CO_2 emissions are not significantly different for PCs based on age but the more recent fleet of PTs tends to have smaller weight and lower CO_2 emission rates than older PTs. Thus, driving cycles and vehicle type have the most influence on CO_2 emission rates, with ambient conditions and vehicle age having secondary influence.

For cycle average NO_x emission rates, the effect of model year and applicable emission standard is the most dominant factor, leading to reductions in NOx of approximately 80% to 90% for newer versus older vehicles. The second most important factor is vehicle type, with

PCs estimated to have 60% to70% lower NOx emission rates than PTs for a comparable model year. Emission rates at moderate cycle average speed are 55% lower than at low speed. Variability in selected ambient conditions leads to 24% variability in emission rates. Thus, regulatory tier, vehicle type, and driving cycle are key contributors to variability in NOx emission rate, with ambient conditions having a secondary influence.

CONCLUSIONS

Case studies of combination of vehicle type, emission standards, and ambient conditions show the interactive impact of factors in emissions. Difference between vehicle types is larger for Tier 2 vehicles for NO_x. Emission factors increase more at low average speed when temperature increases. Sensitivity analysis has been made for CO_2 and NO_x based on empirical vehicle type, age, and ambient conditions. Both pollutants are sensitive to temperature, average speed, and standard deviation of speed. Only NOx is sensitive to humidity. None of the pollutants is sensitive to average acceleration, since the average acceleration of an empirical driving cycle is usually around 0 mph/second.

Sensitivity of emission factors to different source of variability is ranked based on empirical condition data. The ranked source of variability provides some insight for the focus of future study design. The source of variability at top rank could be considered as the most important factor to focus on in future study if time and resources are limited. Emission control method related to the top ranked source of variability can also be considered as the most effective way to reduce emissions.

As data become available for tier 3 vehicles in future years, this analysis could be extended and updated. The methods here could be extended to more vehicle types, including light commercial trucks, single unit short haul truck, combination long haul trucks, transit buses, motorcycles, and hybrid electric vehicles.

Although the current is based on light duty vehicles which is comprising large amount of vehicle in U.S., the performance of emissions versus four factors may be different for other vehicle types, and vehicles in other countries. The current evaluation is based on U.S. vehicles and can be implemented for vehicle in other countries in future.

TABLE V-1 Scenarios of Case Studies, Input Assumptions, and Selected Results

Case Study Definition			Case Study Inputs [a]		Selected Summary Outputs			
Case ID	Vehicle Type [b]	Tier	Temper -ature (°F)	Humidity (%)	CO_2 Average (g/mi)	CO_2 CI[c] (g/mi)	NO_x Average (g/mi)	NO_x CI (g/mi)
PC1-65	PC	1	65	37	357	±4	0.45	±0.004
PC1-75	PC	1	75	58	385	±5	0.54	±0.008
PC1-95	PC	1	95	80	446	±7	0.72	±0.020
PC2-65	PC	2	65	37	358	±4	0.04	±0.001
PC2-75	PC	2	75	58	385	±5	0.05	±0.001
PC2-95	PC	2	95	80	447	±7	0.06	±0.002
PT1-65	PT	1	65	37	510	±6	1.09	±0.017
PT1-75	PT	1	75	58	547	±7	1.27	±0.014
PT1-95	PT	1	95	80	636	±9	1.68	±0.038
PT2-65	PT	2	65	37	429	±5	0.17	±0.002
PT2-75	PT	2	75	58	462	±6	0.20	±0.002
PT2-95	PT	2	95	80	535	±7	0.27	±0.007
EM	Em[d]	Em	Em	Em	428	±10	0.38	±0.037

[a] For each case, the output is based on 591 driving cycles.

[b] PC = Passenger Car; PT = Passenger Truck

[c] CI: 95% confidence interval of the mean

[d] Em: Empirical Case Study based on 100 vehicles of which 66 are PCs and 34 are PTs. For each vehicle, the observed real-world driving cycles and ambient conditions are used as inputs. The observed real-world temperature varied from 31 °F to 90 °F, and the observed relative humidity varied from 17% to 100%.

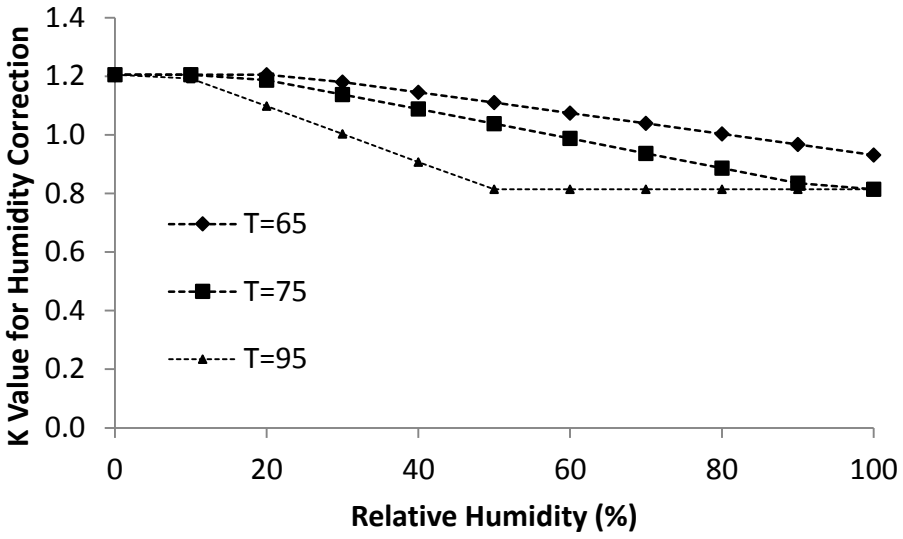
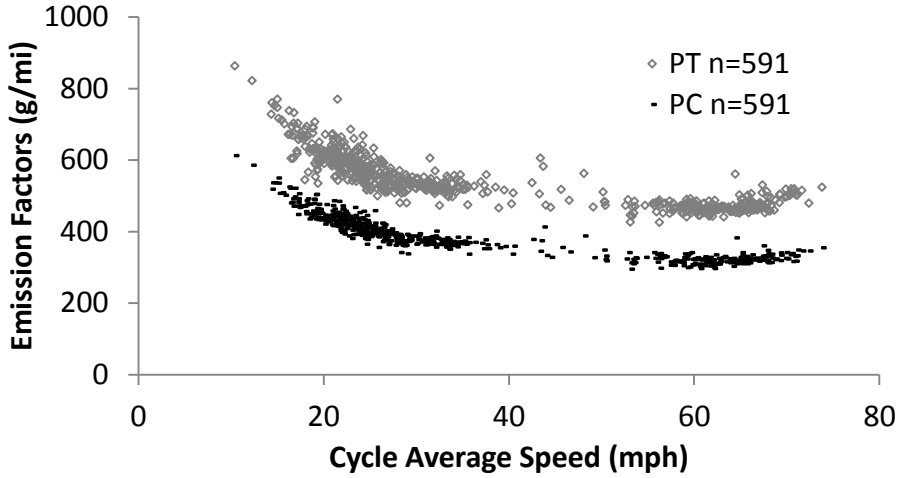
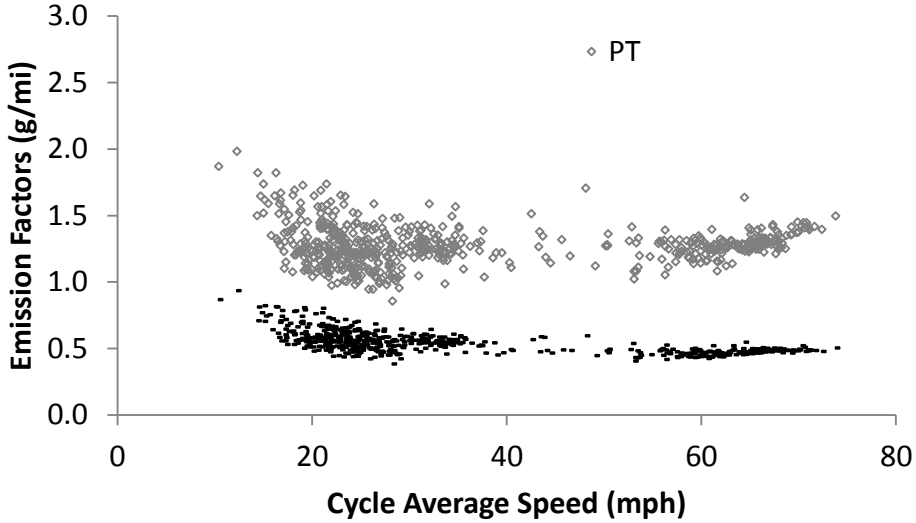


Figure V-1 K Value of Humidity Correction for NOx Cycle Average Emission Factors under Temperature of 65 ºF, 75 ºF, and 95 ºF.



(a) CO_2



(a) NO_x

Figure V-2 CO_2 and NOx Cycle Average Emission Factors for Tier 1 (Model Year 2001) Passenger Cars (PCs) and Tier 1 (Model Year 2001) Passenger Truck (PTs) at 75 ºF /58% Relative Humidity (Cases PC1-75 and PT1-75) based on 591 Real World Cycles

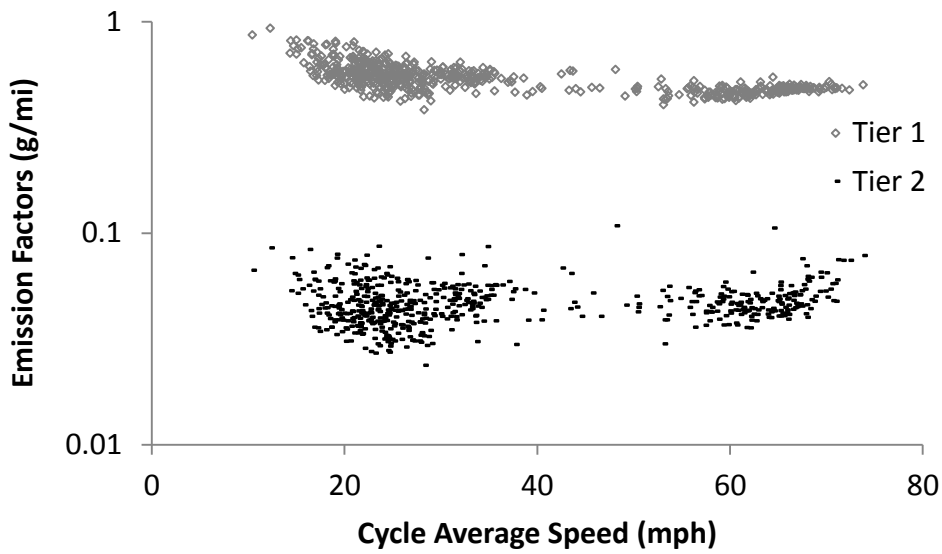
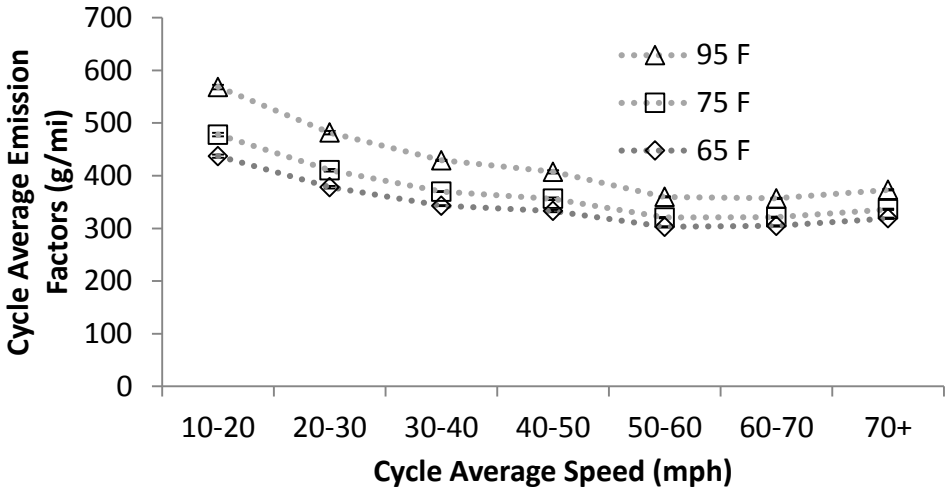
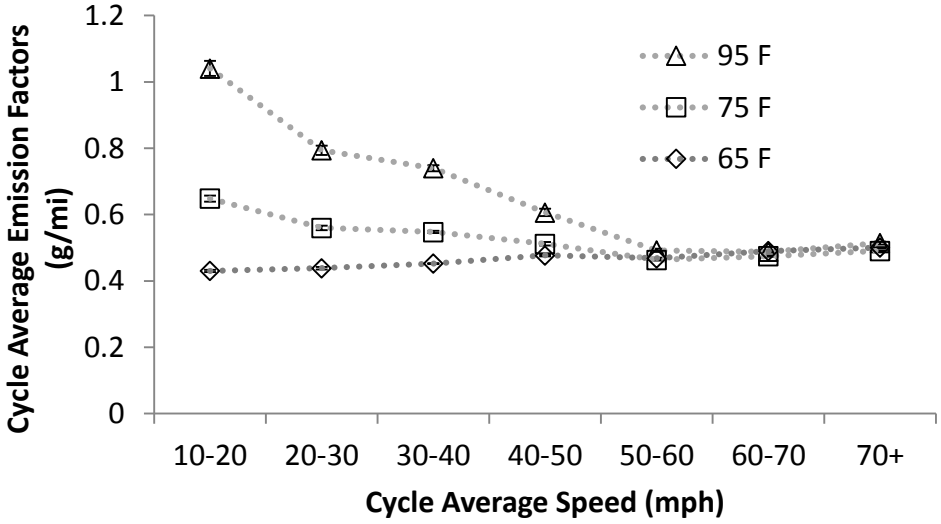


Figure V-3 NO_x Cycle Average Emission Factors for Tier 1 (Model Year 2001) Passenger Cars and Tier 2 (Model Year 2011) Passenger Cars at 75 ºF /58% Relative Humidity (Cases PC1-75 and PC2-75) based on 591 Empirical Driving Cycles



(a) CO_2



(b) NO_x

Figure V-4 Comparison of Trends in CO_2 and NO_x Cycle Average Emission Factors versus Cycle Average Speed for Tier 1 (Model Year 2001) Passenger Car for Three Ambient Conditions: 65 ºF /37% Relative Humidity (Case PC1-65) ;75 ºF /58% Relative Humidity (Case PC1-75), and 95 ºF c /80% Relative Humidity (Case PC1-95), based on 591 empirical driving cycles

TABLE V-2 Standardized Rank Regression Coefficients (SRRC) of Regression Model Based on Empirical Vehicle Type, Age, and Ambient Conditions

Vehicle Type, Sample Size, Coefficient of Determination, and Explanatory Variables	Values of the Coefficient of Determination (R2) and of the Standardized Rank Regression Coefficients (SRRCs) by Vehicle Type and Pollutant[a]			
Tier 1 Passenger Car	**Speed < 50 mph**		**Speed >=50 mph**	
Sample Size: 141 cycles	**CO_2**	**NO_x**	**CO_2**	**NO_x**
R^2	0.90	0.07	0.7	NS
Temperature SRRC	8.5	11.4	4.9	NS
Relative Humidity SRRC	NS[b]	NS	NS	NS
Cycle Average Speed SRRC	-29.5	NS	4.9	NS
Standard Deviation of Speed SRRC	4.4	NS	10	NS
Standard Deviation of Acceleration SRRC	7.1	NS	NS	NS
Tier 2 Passenger Car	**Speed < 50 mph**		**Speed >=50 mph**	
Sample Size: 246 cycles	**CO_2**	**NO_x**	**CO_2**	**NO_x**
R^2	0.75	NS	0.34	NS
Temperature SRRC	7.4	NS	6.8	NS
Relative Humidity SRRC	NS	NS	NS	NS
Cycle Average Speed SRRC	-41	NS	8.5	NS
Standard Deviation of Speed SRRC	6.3	NS	NS	NS
Standard Deviation of Acceleration SRRC	9.6	NS	10	NS
Tier 1 Passenger Truck	**Speed < 50 mph**		**Speed >=50 mph**	
Sample Size: 60 cycles	**CO_2**	**NO_x**	**CO_2**	**NO_x**
R^2	0.77	0.29	0.56	NS
Temperature SRRC	5.0	NS	NS	NS
Relative Humidity SRRC	NS	NS	NS	NS
Cycle Average Speed SRRC	-8.5	-6.1	2.8	NS
Standard Deviation of Speed SRRC	NS	7.2	4.1	NS
Standard Deviation of Acceleration SRRC	NS	NS	NS	NS

TABLE V-2 Continued

Tier 2 Passenger Truck	Speed < 50 mph		Speed >=50 mph	
Sample Size: 144 cycles	CO_2	NO_x	CO_2	NO_x
R^2	0.52	0.33	0.21	0.14
Temperature SRRC	10.5	10.9	5.8	NS
Relative Humidity SRRC	-9.0	-10.5	NS	-4.7
Cycle Average Speed SRRC	-14	NS	NS	NS
Standard Deviation of Speed SRRC	NS	5.0	NS	NS
Standard Deviation of Acceleration SRRC	NS	NS	NS	NS

[a]. SRRC values and R^2 values are shown in this table for four groups of vehicles in Tier 1 and 2, PCs and PTs separately.

[b]. NS: not significant

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PART VI **CONCLUSIONS**

SUMMARY OF FINDINGS

- The trends in MOVES estimated emission factors with respect to driving cycles, vehicle type, regulatory tier, and related factors such as cycle average speed, road type, vehicle age, and mileage accumulation are qualitatively consistent with those observed in independent empirical data. The magnitude of CO_2 cycle average emission rates is similar for MOVES and empirical data. The magnitude of cycle average emission rates for NO_x, CO, and HC is typically higher for MOVES than for empirical data, which is attributed to the reported incorporation of high emitting vehicles into the MOVES default OpMode rate databases.
- The performance envelope of speed and acceleration was found to be approximately similar for PC, PT, and HEV vehicle types, with slightly wider ranges of acceleration at higher speeds for PTs.
- The real-world performance envelope was found to be weakly different for PT versus PC, but the absolute differences in the high end accelerations between these vehicle types were relatively small.
- There is weak or suggestive evidence that factors such as transmission type, road grade, and horsepower may affect the performance envelope. Horsepower and curb weight are positive correlated.
- a simplified (or reduced form) version of MOVES has been developed and shown to be highly precise in producing the same cycle average emission rates for a wide variety of vehicle types, vehicle ages, pollutants, and driving cycles. The simplified

model is computationally more simple than MOVES and can easily be encoded as part of a TDM or TSM.

- Emissions are most sensitive to driving cycles, vehicle types, and emission standards. Given the same vehicle type and model year, emissions are more sensitive to temperature and low average speed than high average speed.

  The main contributions of the work here are: 1) this is the first time that MOVES has been evaluated for a wide range of real-world driving cycles based on independent field measurements of emissions; 2) a method to evaluate speed and acceleration distributions of driving cycles has been developed and applied to real-world driving cycles; 3) a simplified emission model that runs 3,000 times faster than MOVES and provides accurate emission rate estimates has been developed to couple with s TSM, and 4) this is the first time that sensitivity of emission factors to multiple variables has been systematically evaluated and the interactive effect of the multiple variables has been quantified.

CONCLUSIONS

- MOVES has the capability of estimating accurate emission factors and reflecting the relative changes in emissions versus sources of variability.
- The consistency in the performance envelope suggests that it is possible to identify typical values of high end acceleration associated with a particular speed, which in turn can be used either to calibrate or evaluate speed trajectories predicted by TSMs.

- The method used here to quantify the performance envelope for real world data can also be applied to simulated 1 Hz trajectories from TSMs to enable comparisons and determination of whether TSM simulated trajectories are realistic.
- The simplified model will be incorporated within a traffic simulation model (TSM) to estimate the impact on emissions of alternative transportation infrastructure, control strategies, and vehicle mix. Therefore, the simplified model is important for research in transportation and air quality management.
- The evaluation of variability of different sources can help develop emission inventories. It is practical to figure out the most sensitive factors when developing emission inventories based on limited sample size or ambient conditions.

LIMITATIONS

- Empirical data of emissions and vehicle activities were measured based on low to moderately priced production cars. No high performance "supercars" were included in the sample.
- The empirical data and MOVES comparison did not include motorcycles, or large trucks.

RECOMMENDATIONS

- Future version of MOVES could add hybrid electric vehicle as a new vehicle type.
- Future measurement could be conducted on high performance "supercars" and heavy duty vehicles for emissions and vehicle activity.

- Evaluation of relationship between performance envelope of speed and acceleration and driver's gender could be an interesting topic. The performance could be evaluated with regard of emissions and driving safety.
- Future work to assess the observable performance envelop response to traffic incidents and ambient conditions (rainy day, snowing day) is recommended.

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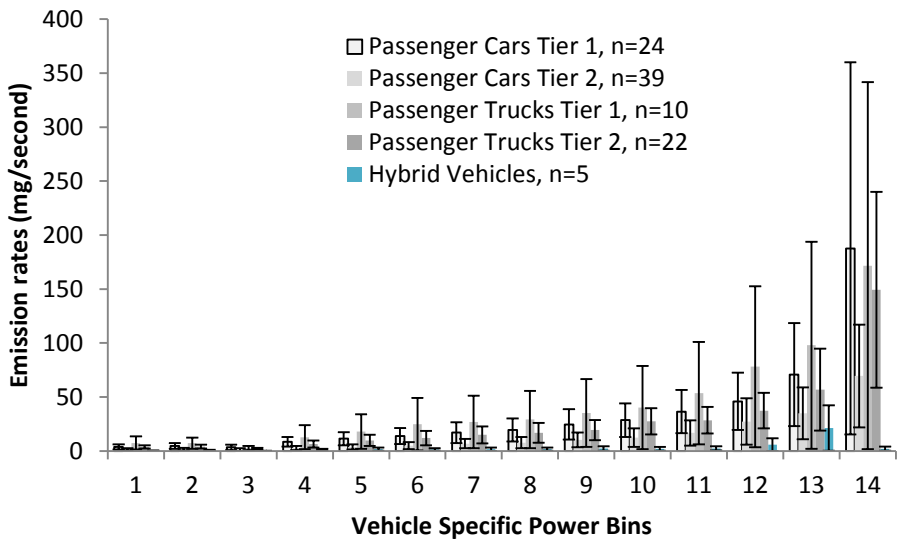
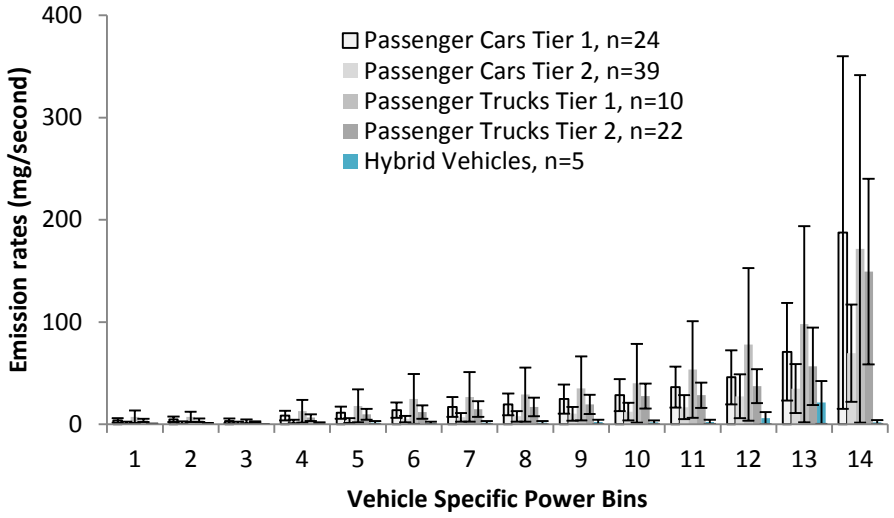
APPENDICES

APPENDIX A SUPPORTING INFORMATION FOR PART II

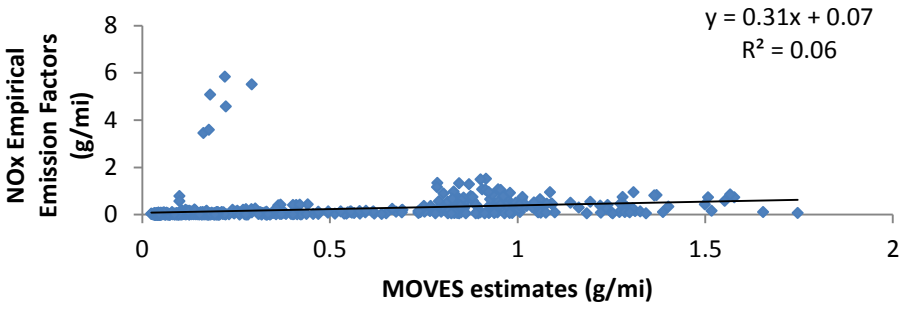


(c) CO



(d) HC

Figure 1 Average of CO and HC VSP Modal Emission Rates for Passenger Cars (PCs), Passenger Trucks (PTs), and Hybrid Electric Vehicles (HEVs)



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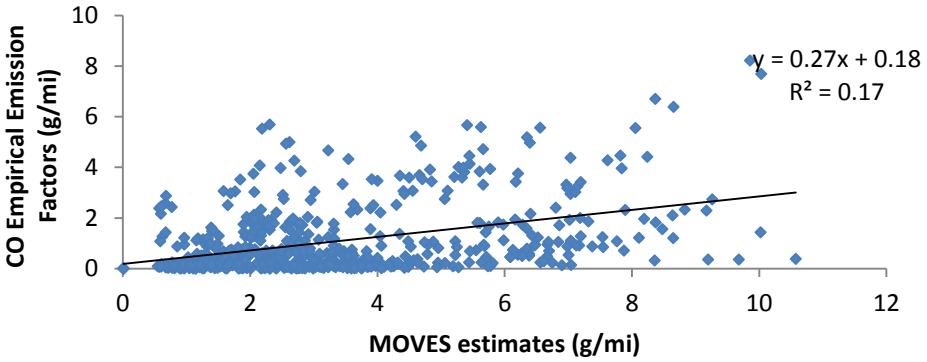
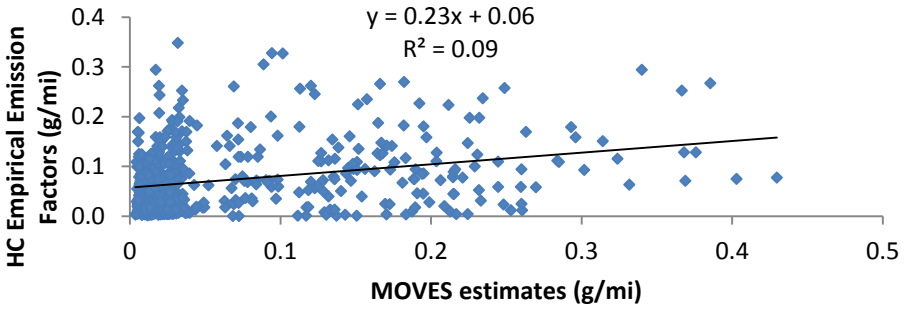
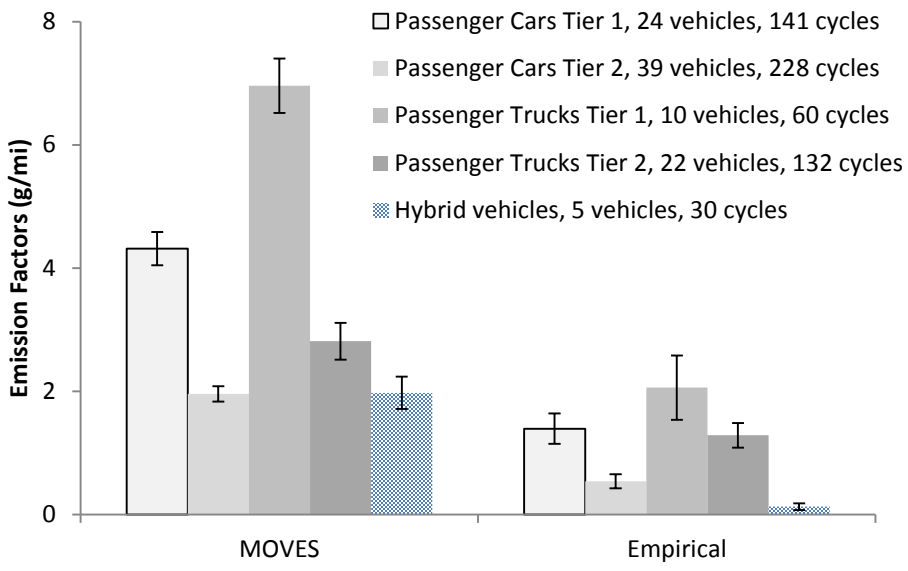


(d) CO

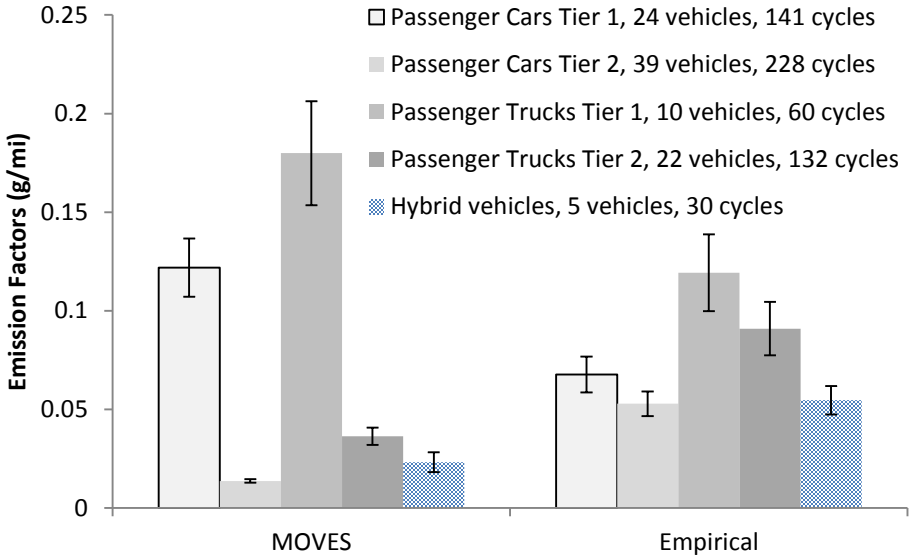


(e) HC

Figure 2 Empirical CO and HC Emission Factors vs MOVES Estimates of 100 Vehicles of All Driving Cycles

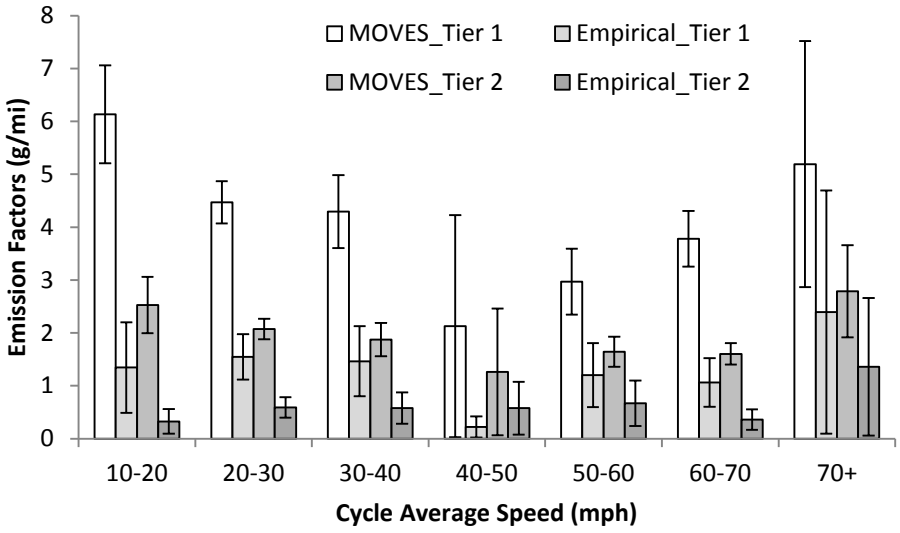


(c) CO

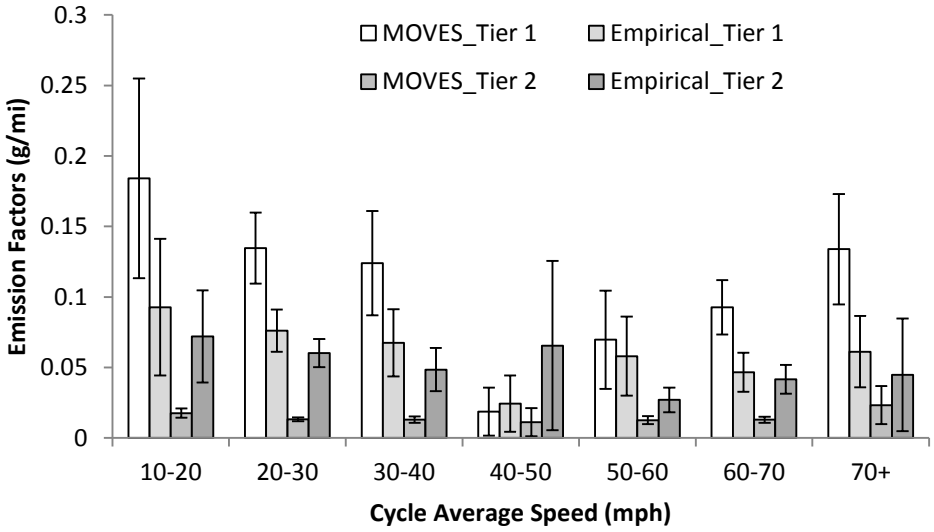


(d) HC

Figure 3 Average CO and HC Emission Factors of PCs, PTs, and HEVs for MOVES and Empirical



(c) Passenger Cars CO



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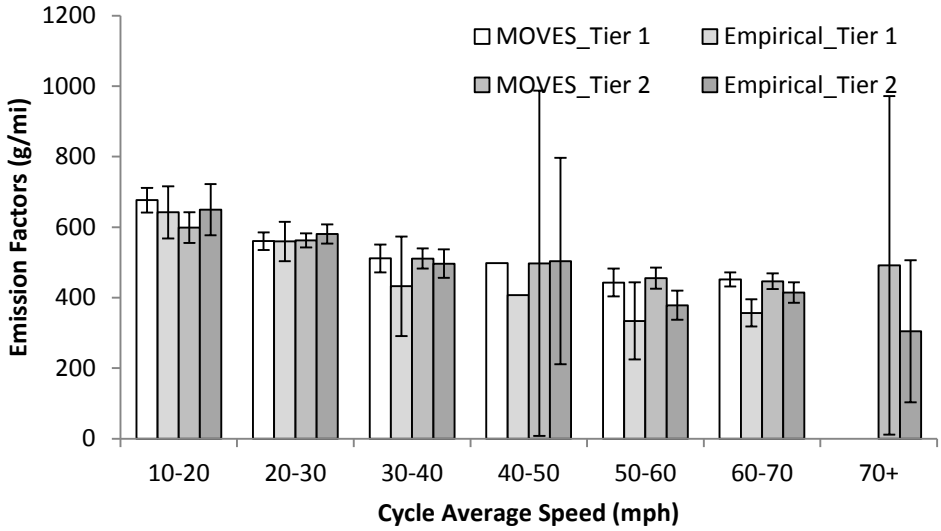
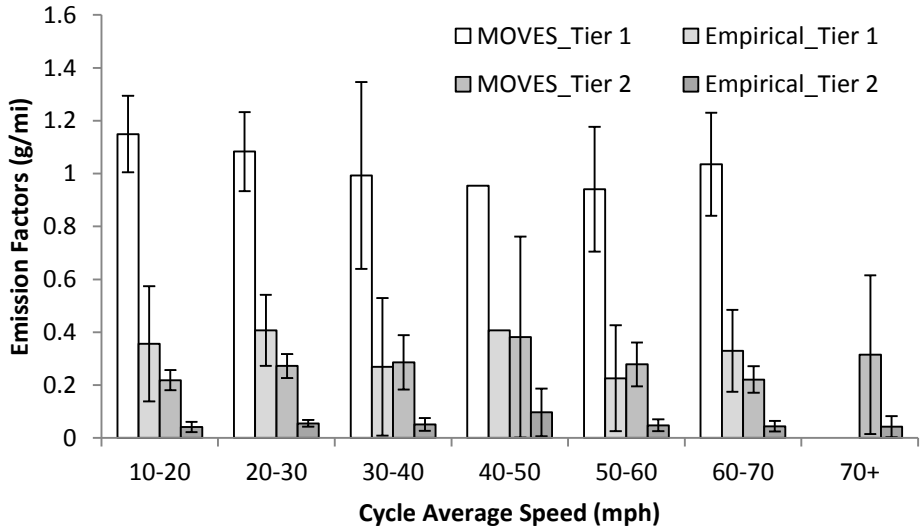
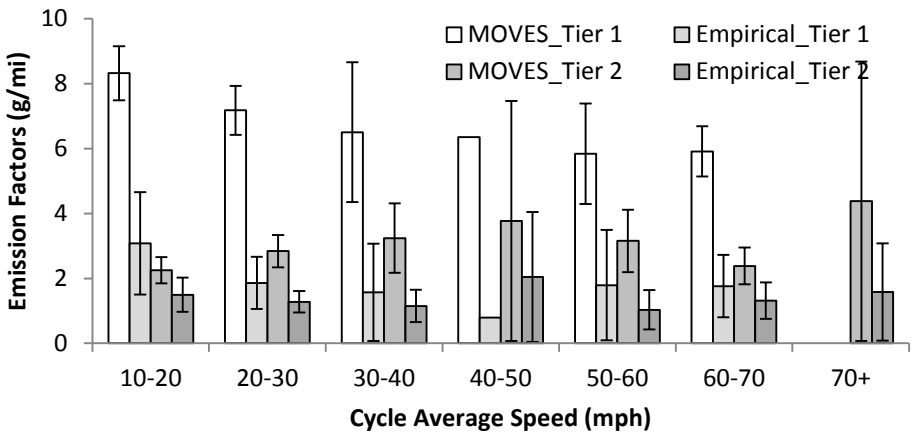


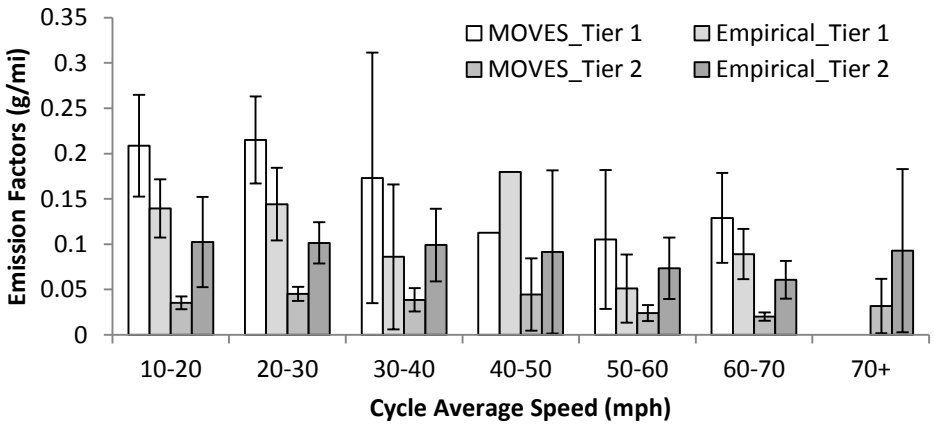
(e) Passenger Trucks CO_2



(f) Passenger Trucks NOx

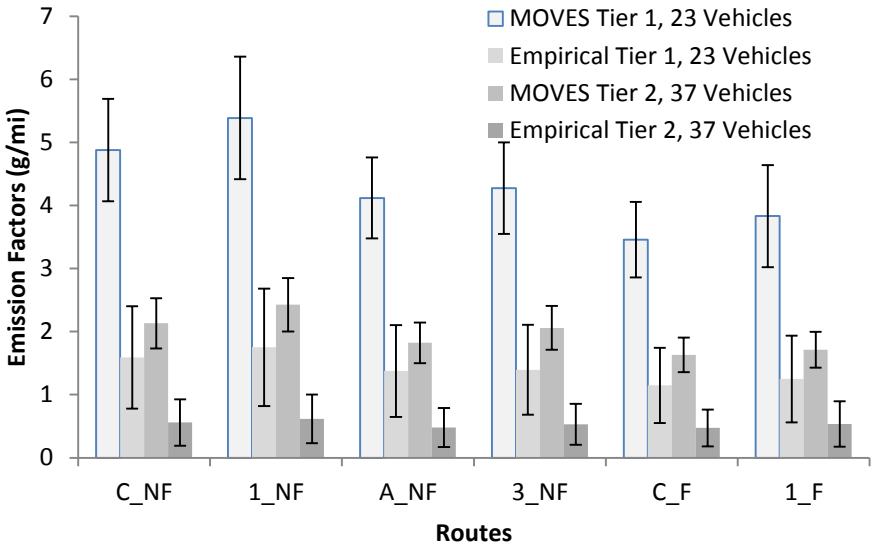


(g) Passenger Trucks CO



(h) Passenger Trucks HC

Figure 4 Average CO_2, NO_x, CO, and HC Emission Factors of Cycle Average Speed for MOVES and Empirical Data for Passenger Cars and Passenger Trucks for Tier 1 and Tier 2



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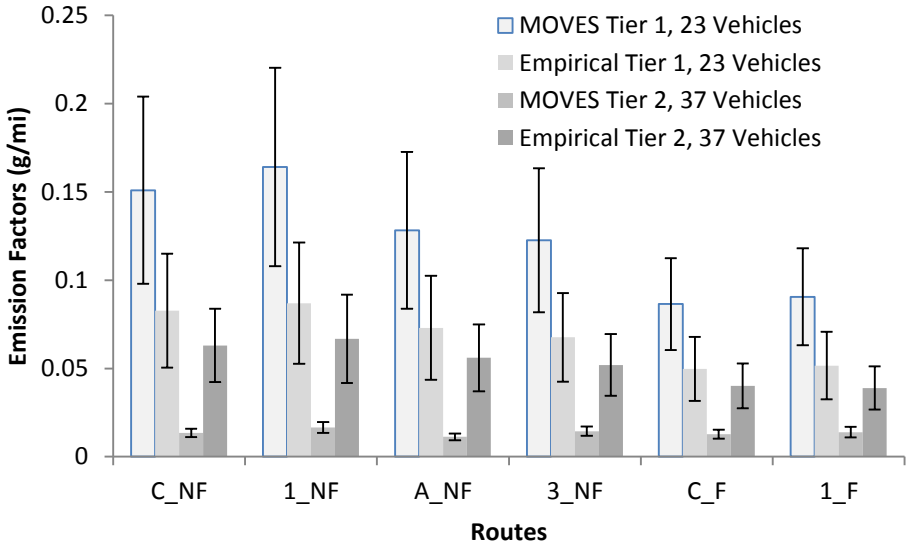
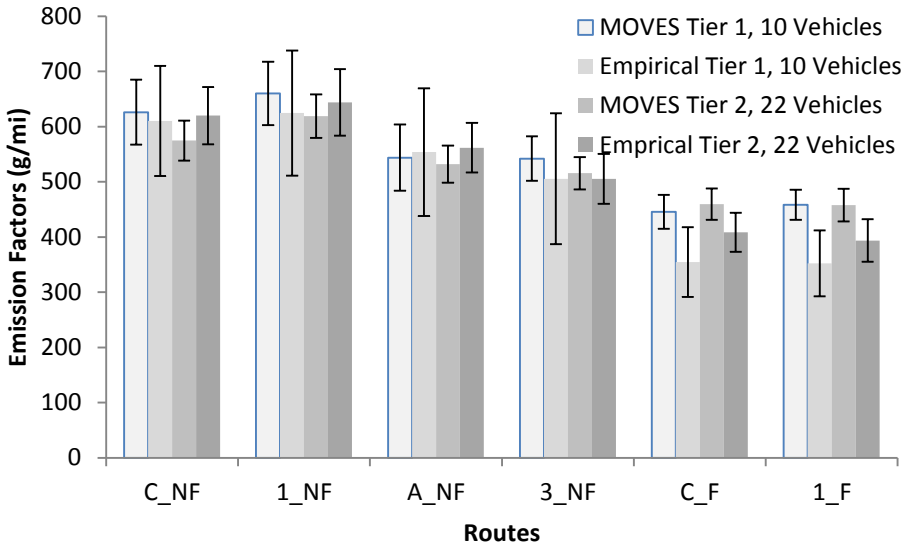
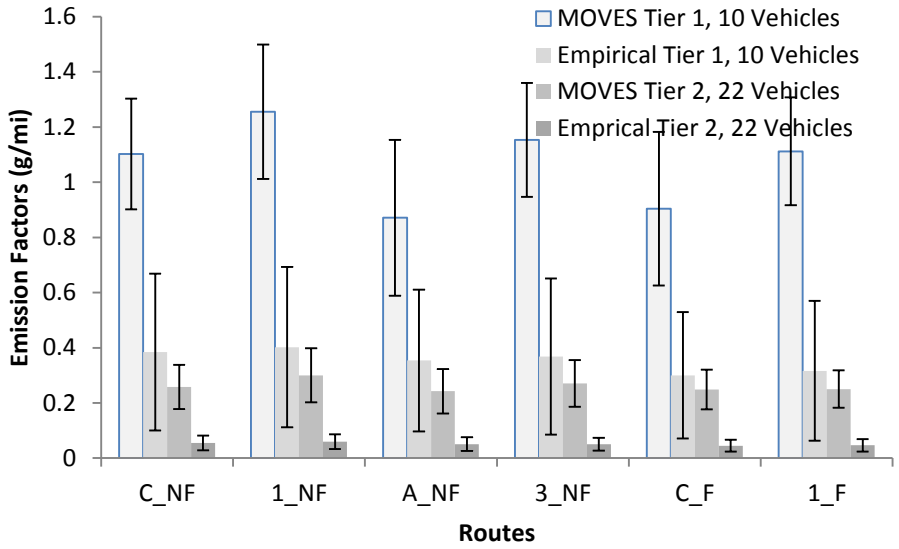


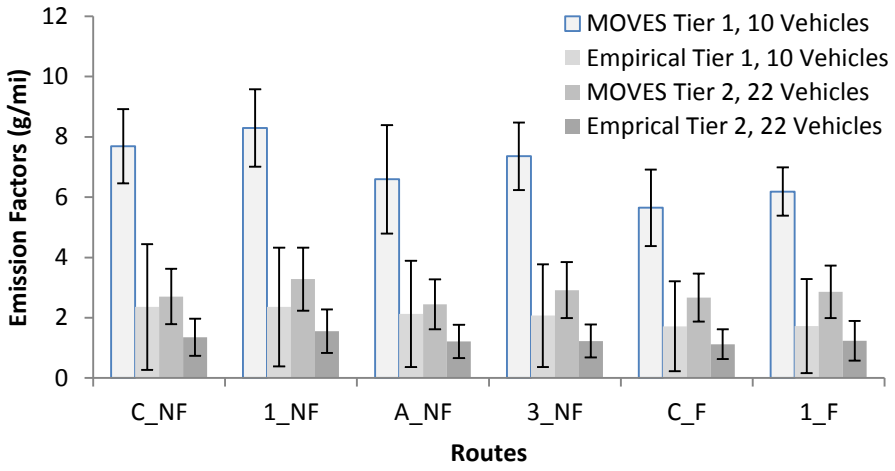
(d) Passenger Cars HC



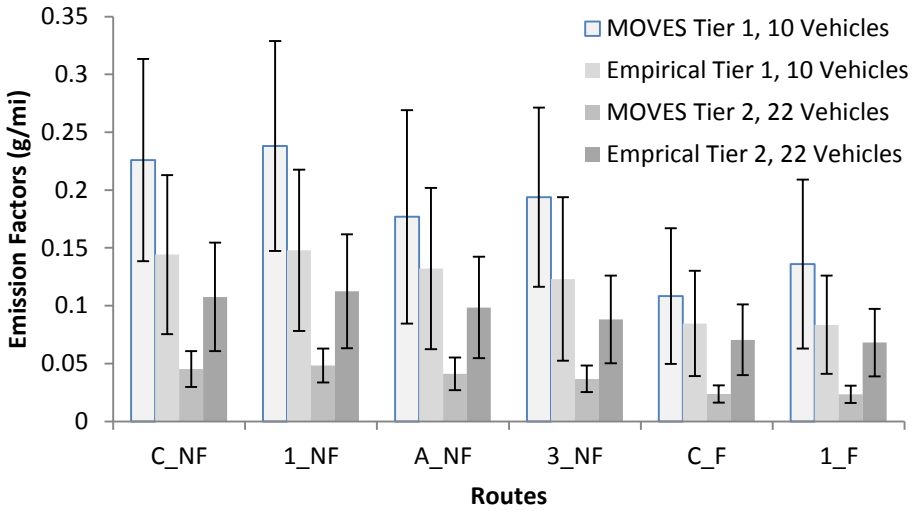
(e) Passenger Trucks CO_2



(f) Passenger Trucks NOx



(g) Passenger Trucks CO



(h) Passenger Trucks HC

Figure 5 Average CO_2, NO_x, CO, and HC Emission Factors of Road Types for MOVES and Empirical Data for Passenger Cars and Passenger Trucks for Tier 1 and Tier 2

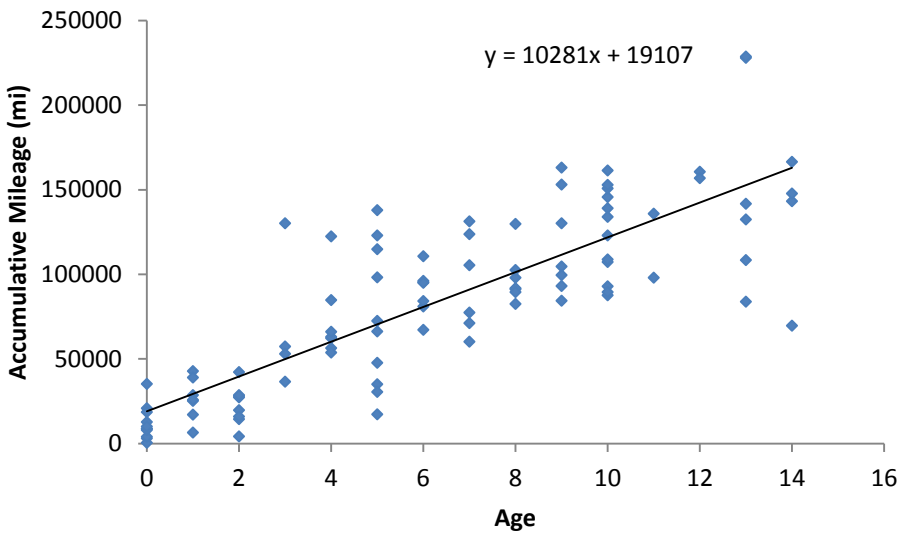


Figure 6 Vehicle Age versus Accumulative Mileage for 100 Vehicles

MOVES Emission Factor =f(age)

TABLE 1 MOVES estimates for Tier 1 PC, n=141

	CO2	NOX	CO	HC
R^2	NOT SIG 0.003	0.43	0.33	0.41
Intercept	NOT SIG	-0.21	0.26	-0.12
age	NOT SIG	0.088	0.38	0.023

TABLE 2 MOVES estimates for Tier 2 PC, n=228

	CO2	NOX	CO	HC
R^2	0.03	0.69	0.51	0.57
Intercept	360	0.027	1.05	0.0067
age	3.6	0.017	0.24	0.0019

TABLE 3 MOVES estimates for Tier1 PT, n=60

	CO2	NOX	CO	HC
R^2	NOT SIG 0.087	NOT SIG 0.072	NOT SIG 0.077	0.37
Intercept	NOT SIG	NOT SIG	NOT SIG	-0.36
age	NOT SIG	NOT SIG	NOT SIG	0.051

TABLE 4 MOVES estimates for Tier 2 PT, n=132

	CO2	NOX	CO	HC
R^2	0.16	0.48	0.37	0.36
Intercept	482	0.12	1.46	0.017
age	12	0.040	0.37	0.0054

Empirical Emission Factor =f(age, mileage, age*mileage) for CO2, NOX, CO, HC

TABLE 5 Empirical data for Tier 1 PC, n=141

PC_TIER I	CO2	NOX	CO	HC
R^2	NOT SIG 0.07	0.12	0.25	0.21
Intercept	NOT SIG	-1.0	-6.6	-0.14
age	NOT SIG	0.11	0.55	0.012
Mileage	NOT SIG	0.00001	0.00008	0.000002
A*M	NOT SIG	-0.0000008	-0.000006	-0.0000001

TABLE 6 Empirical data for Tier 2 PC, n=228

PC_TIER II	CO2	NOX	CO	HC
R^2	NOT SIG 0.03	NOT SIG 0.04	0.07	0.17
Intercept	NOT SIG	NOT SIG	0.43	0.019
age	NOT SIG	NOT SIG	0.06	0.02
Mileage	NOT SIG	NOT SIG	0.000005	0.0000005
A*M	NOT SIG	NOT SIG	NOT SIG	-0.0000002

TABLE 7 Empirical Data for Tier 1 PT, n=60

PT_TIER I	CO2	NOX	CO	HC
R^2	NOT SIG 0.07	0.23	NOT SIG 0.02	0.29
Intercept	NOT SIG	NOT SIG	NOT SIG	NOT SIG
age	NOT SIG	0.10	NOT SIG	NOT SIG
Mileage	NOT SIG	0.000004	NOT SIG	0.000001
A*M	NOT SIG	NOT SIG	NOT SIG	NOT SIG

TABLE 8 Empirical Data for Tier 2 PT, n=132

PT_TIER II	CO2	NOX	CO	HC
R^2	NOT SIG 0.05	0.44	NOT SIG 0.06	0.18
Intercept	NOT SIG	0.0013	NOT SIG	NOT SIG
age	NOT SIG	0.010	NOT SIG	0.005
Mileage	NOT SIG	0.0000006	NOT SIG	0.0000006
A*M	NOT SIG	NOT SIG	NOT SIG	NOT SIG

TABLE 9 Empirical Data for HEV, n=30

PT_TIER II	CO2	NOX	CO	HC
R^2	0.28	0.37	0.91	0.61
Intercept	206	NOT SIG	NOT SIG	0.066
age	38	0.016	-0.16	-0.027
Mileage	NOT SIG	0.0000008	0.000006	-0.0000007
A*M	NOT SIG	-0.0000003	0.000002	0.0000005

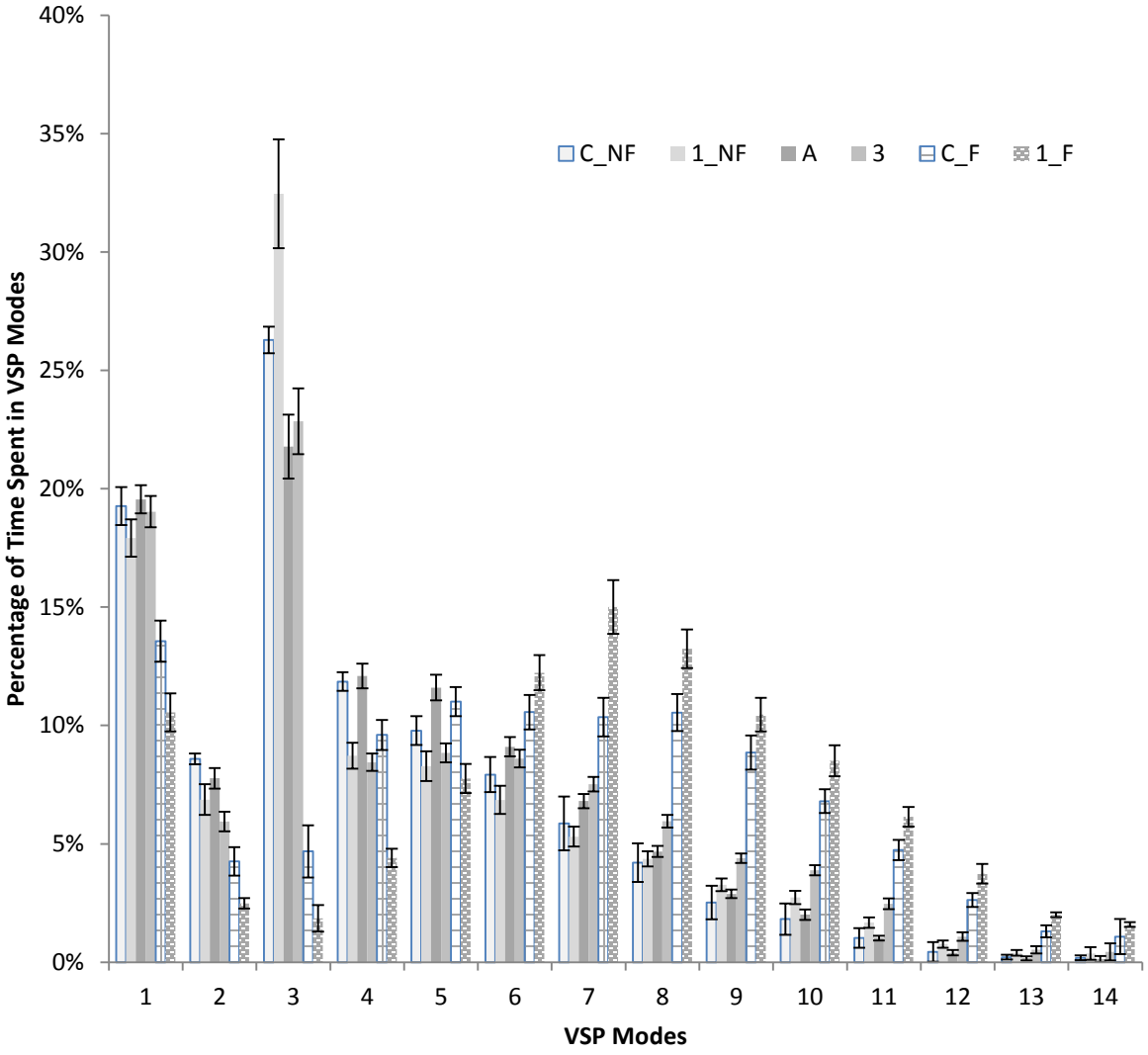


Figure 7 Average Percentage of Time Spent in VSP Modes for Six Driving Cycles

Emission Factors for Hybrid Vehicles

For MOVES, emission factors are estimated based on entire driving cycles for engine on + engine off.

For empirical data, emission factors are estimated based on VSP modal emission rates, and driving cycles for engine on + engine off.

$$EF_{p,e} = \frac{\sum_1^{14} ER_{i,p,e} \times t_i}{L}$$

$EF_{p,e}$ = empirical cycle average emission factor, grams per mile

$ER_{i,p,e}$ = empirical modal emission rates for the ith VSP mode, grams per second

t_i = time spent on the ith VSP mode, second (engine on + engine off)

L = length of the cycle, mile (engine on + engine off)

p = pollutants of CO_2, NOx, CO, HC