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Variability and Uncertainty in Highway Vehicle Emission Factors

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ABSTRACT

Highway motor vehicles contribute significantly to total emissions of nitrogen oxides (NO_X), carbon monoxide (CO), and hydrocarbons (HC). However, relatively little attention has been given to the proper quantification of variability and uncertainty in highway vehicle emission factors. Variability is the diversity of emissions values for different vehicles and for individual vehicles for different driving behaviors, maintenance, fuels, and other factors. Uncertainty arises from a lack of complete knowledge regarding the true value of emission factors, such as due to limited availability of data, measurement errors, and nonrepresentativeness of measured values with respect to true on-road vehicle emissions. In this paper, we summarize the results of two studies aimed at quantifying both variability and uncertainty. In one study, we developed probabilistic estimates of inter-vehicle variability, and of uncertainty in fleet average emissions, for a selected set of light duty gasoline vehicle (LDGV) emission factors associated with the Mobile5a model. In the second study, we measured on-road CO and HC emissions of school buses and transit buses at several sites using remote sensing. The implications of the emission factor uncertainty estimates for management and reporting of emission inventories and for development of air quality management strategies are discussed.

INTRODUCTION

Decision-making about emission control strategies requires good information regarding emissions and their impact on ambient air quality. Emission inventories (EIs) are used for a variety of purposes, including: (a) identification of annual emission trends; (b) comparison of current to baseline emissions for compliance purposes; and (c) prediction of ambient pollutant concentrations using air quality models (AQMs). Biases and random errors in the EIs can lead to erroneous conclusions regarding trends in emissions and the relationships between emissions and ambient air quality.

In this paper, we provide an overview of previous work regarding quantification of uncertainty in emission factors and emission inventories. Then, we focus on sources of variability and uncertainty regarding emissions of CO, NO_x, and hydrocarbons (HC) from highway motor vehicles. The results of two recent studies performed are provided. One is a re-evaluation of portions of the Mobile5a emission factor model. The other is a remote-sensing study of on-road emissions from selected types of buses. Both studies provide information regarding variability and uncertainty in highway vehicle emissions.

VARIABILITY AND UNCERTAINTY IN EMISSION INVENTORIES

The U.S. Environmental Protection Agency (EPA), the National Academy of Sciences (NAS), and others have recently placed increased emphasis on the important role of probabilistic analysis in environmental assessments.[1,2] In May of 1997, EPA issued a "Policy for Use of Probabilistic Analysis in Risk Assessment".[3] The policy supports "good scientific practice in quantifying uncertainty and variability." EPA's new policy is based upon the report of an EPA-sponsored workshop of nationally-known experts in probabilistic methods and a supporting document prepared within the agency regarding guiding principles.[4,5] These recent activities are indicative of increasing acceptance of quantitative methods for addressing both variability and uncertainty in environmental assessments.

Uncertainty is a lack of knowledge about the true value of a quantity. Uncertainties in emissions are typically attributable to: (1) random measurement errors (lack of "precision"); (2) systematic errors (bias or lack of "accuracy") such as would be caused by imprecise calibration, loss of sample material, spectral interferences in chemical analyses, or use of surrogate data (e.g., laboratory tests of vehicles rather than on-road measurements); (3) lack of empirical basis such as would occur when measurements have not been taken or when estimating emissions for a future source; and (4) human error, such as random mistakes in entering or processing data. *Variability* is a heterogeneity of values across different elements of a population (broadly defined) over time or space. For example, process variability leads to differences in emissions as a function of vehicle design (inter-vehicle variability) and operating conditions (intra-vehicle variability). For a single vehicle, emissions may vary with time due to changes in fuel composition, engine load, random variation in throttle position, failure of pollution control systems, maintenance practices, and so on. While both variability and uncertainty can be described probabilistically, they are distinct concepts.

There have been relatively few reported efforts to quantify uncertainty in EIs. Estimates of uncertainty were developed for the 1980 and 1985 emissions inventories used in the National Acid Precipitation Assessment Program (NAPAP).[6,7] Although uncertainties and systematic errors in EIs used for air quality modeling of tropospheric ozone are acknowledged, specifically for VOC and NO_x emissions, methods for characterizing, evaluating, and managing such uncertainties are lacking. Two previously used methods are qualitative ratings and propagation of errors. Ratings approaches include "A" to "E" emission factor ratings and the Data Attribute Rating System (DARS).[8,9] While DARS can enable comparative qualitative assessments of confidence ratings for emissions inventories, it cannot be used to *quantify* the precision of an inventory. Thus, these methods cannot be used to evaluate the robustness of a decision to uncertainty. Other efforts have focused on characterizing the mean and variance of emission estimates and using simplified approaches for combining uncertainties in activity and emission factor data to arrive at an aggregate uncertainty estimate for the entire inventory.[10,11,12] Because of the simplifying assumptions employed to enable analytical calculations of overall uncertainty in the inventory, these approaches typically require that only normal or lognormal probability distribution models be used to describe uncertainty and that all inputs to the inventory must be modeled as statistically independent of each other. The applications of these approaches suffer from other shortcomings, including failure to: distinguish between variability and uncertainty; use appropriate averaging times; properly analyze data of small sample sizes; and employ proper protocols in eliciting expert judgments.

Although limited in many respects, previous work does illustrate the importance of considering uncertainty in an EI. In one study, total NO_x emissions were estimated to be uncertain by ± 20 percent, while VOC EIs were estimated to be uncertain by ± 30 percent.[11] These are likely to be underestimates. For example, 40 percent of total VOC emissions are estimated to come from mobile sources. A study by Radian of emissions in Western states estimated the standard deviation of VOC emissions from motor vehicles to be 75 percent of the mean value.[12] The large standard deviation implies that the distribution of emissions is positively skewed. It is possible, but unclear, that this estimate may represent inter-vehicle variability and not uncertainty in the fleet average.

The actual range of uncertainty in emissions depends upon the type of question being addressed, which in turn motivates the type of temporal and spatial averaging to be used. For example, estimates of annual average NO_x emissions for a specific intermediate-loaded coal-fired power plant based on several years of continuous emission monitoring (CEM) data would have comparatively little uncertainty. However, estimates of the emissions for a given hour of a given weekday (e.g., emissions during an ozone episode on a future Tuesday from 8 AM to 9 AM) will have more uncertainty due to short-term variation in plant load and operating conditions. Similarly, estimates of gridded, hourly NO_x and VOC emissions required for AQMs will be more uncertain than would annual average estimates for an entire state.

The distinctions between variability and uncertainty are illustrated by Frey using a two-dimensional probabilistic simulation framework.[13] For example, there may be uncertainty regarding the selection of a probability distribution that represents variability. A source of uncertainty which can be modeled using known statistical techniques is random sampling error. If data are a representative sample of an unknown population and are obtained at random, then there is uncertainty in estimates of any statistic used to summarize the data. Hence, there may be uncertainty regarding the parameters of a probability distribution model selected to represent the data. Furthermore, there may be ambiguity regarding the appropriate type of parametric distribution to use. Frey illustrates this by comparing fitted normal and lognormal distributions, with estimates of uncertainty in the cumulative distribution functions for each type of distribution, for an example environmental data set.[14]

A common example of the use of random sampling error to characterize uncertainty is the development of confidence intervals for mean values. For large sample sizes or for small sample sizes from relatively symmetrically distributed data sets, the sampling distribution of the mean is approximately normal (Gaussian). The standard error of the mean is characterized based upon the standard deviation of the population sample divided by the square root of the sample size. Thus, the standard error will be large if the sample size is small or if the population sample has a large standard deviation. Methods for characterizing uncertainties in a variety of statistics are described elsewhere.[15,16] Numerical simulation methods, such as the bootstrap, can be used to estimate sampling distributions for the mean in situations where the assumption of normality would be in error.[17]

In the context of emission factor development, data sets from emissions measurements may typically be used to characterize inter-vehicle variability based upon resampling of the data, step-wise empirical distributions, or fitted parametric distributions. The sampling distribution of the mean can be used to characterize uncertainty in the average emissions from a population of similar sources (e.g., a fleet of vehicles of similar design). In some cases, the sampling distribution for the mean may have a sufficiently large range of values such that it dominates any other sources of uncertainty, such as measurement error. In other cases, the use of a sampling distribution to represent uncertainty may lead to under-estimates of uncertainty or mis-estimates of uncertainty if other sources of uncertainty are more important and/or if the data are not truly a representative random sample. In the absence of information regarding a datum for the true value of emissions, biases can be difficult to quantify. It may be possible to evaluate the representative of a dataset by comparison with other datasets; however, in practice expert judgment is required to assess the adequacy of a dataset in representing a population of interest.

VARIABILITY AND UNCERTAINTY IN MOBILE SOURCE EMISSIONS

Bishop *et al.* describe the variability in emissions estimates for motor vehicles observed using a variety of testing methods.[18] They report on similarities in the observed test-to-test variability in emissions measurements using several types of tests, including the Federal Test Procedure (FTP) and IM240 driving cycles, remote sensing, and idle tests. Their conclusions are that individual vehicles may exhibit substantial variability from one test to another in any of these tests and, therefore, that the observed variability in repeated measurements for individual vehicles is not primarily due to limitations of the test methods themselves. For light duty gasoline vehicles, factors such as inconsistency in control of the air-to-fuel ratio, due perhaps to malfunctioning oxygen sensors, may be a dominate source of variability.

It has been hypothesized that driver behavior can substantially contribute to variability in emissions. Webster and Shih compared repeated measurements using the IM240 driving cycle test in which a test driver was asked to produce deliberate speed errors without violating the allowable plus or minus 2 mph speed tolerance for the standard speed profile.[19] Tests were conducted based upon driving the cycle as smoothly as possible and based upon aggressive driving (e.g., hard accelerations) within the allowable tolerance. In addition, several other drivers were asked to conduct the cycle in a "normal" manner. As an example of the results, the CO emissions from the "smooth" tests of a 1987 Plymouth Reliant were approximately 67 percent of those from "normal" testing, while the "rough" tests yield emissions 750 percent higher than for the normal tests. Thus, these tests indicate that driver behavior, may be responsible for potentially order-of-magnitude differences in emissions. Shih *et al.* are studying the effect of driver behavior on throttle position, but note that enrichment events associated with operation of light duty gasoline vehicles equipped with catalyts complicate the interpretation of test results in terms of predicting emissions.[20]

These studies suggest that a substantial amount of inter-vehicle and even intra-vehicle variability in emissions may be unexplainable by factors often used as independent variables in trip-based emission factor models, such as the average speed of a driving cycle. Modal emission factor models which attempt to estimate engine loads may also be unable to completely eliminate unexplained variability due, for example, to tolerances within which throttle position is controlled.

Singer and Harley developed a highway vehicle emission inventory based upon remote sensing data. As noted later, remote sensing enables measurements of on-road vehicles under actual driving conditions. They report emission uncertainty estimates of plus or minus 20 percent for automobiles and plus or minus 30 percent for light trucks.[21]

EMISSIONS MEASUREMENTS AND TRIP-BASED EMISSION FACTOR MODELS

The vehicle emission factor models used for regulatory purposes, such as Mobile5a and EMFAC in California, are trip-based. In typical practice, only one or two trip-based driving cycle tests may be performed on a given vehicle. Therefore, there are relatively few repeat test data readily available from which to make inferences of intra-vehicle variability in emission factors derived from these driving cycle tests. However, there are data available regarding inter-vehicle variability within the small fleets of similar vehicles that have been tested using the FTP and other cycles for purposes of providing data for input to the Mobile series of emission factor models. In order to understand the role of these data sets in model development, it is useful to briefly review the structure of the Mobile model.[22,23,24]

The MobileX series of models are predicated upon a Base Emission Rate (BER), which in principle would be estimated from measurements of Bag 2 of the FTP for zero mileage vehicles (zero miles on the odometer). Bag 2 is the portion of the FTP that is in "warm stabilized" operating mode. However, because of the limited availability of such data, the EPA decided to use data from a similar, shorter, and more widely used test, the IM240 driving cycle, to estimate the FTP Bag 2 emissions. The IM240 test has been administered to thousands of vehicles, compared to the hundreds of vehicles for which Bag 2 data were available. By measuring a set of vehicles on both the FTP Bag 2 and the IM240, EPA developed a dataset from which to develop regression equations for using IM240 data to predict FTP Bag 2 emissions. Thus, a much larger and presumably more representative set of vehicles are used to characterize the average BERs for a variety of LDGV technology groups. The IM240 data set contains vehicles with a range of odometer readings, which also enables development of "deterioration rate" coefficients representing an assumed linear increase in emissions with increased odometer reading. The BER is inferred from a regression analysis of emissions versus odometer reading in which the emissions are either estimated or extrapolated (if zero mileage data are not included in the data set) from the regression equation for an odometer reading of zero.

The zero-mileage BER is adjusted by multiplicative correction factors. These factors include, for example, speed correction, mileage deterioration, ambient temperature, operating mode (e.g., cold start, warm stabilized, hot start), and others. The point-estimate predictions of Mobile5a are well-known to have a strong sensitivity to variations in the average speed entered by the user. The speed correction factor is based upon an assumed functional form relating average emissions to the average speeds of multiple driving cycles. For example, for LDGV, a total of 11 driving cycles were used to develop the speed correction ratio. The data sets used for this purpose are typically of sample sizes of approximately 100 or less for each of 13 technology groups.

Chatterjee *et al.* evaluated the "error/uncertainty" in predictions of Mobile5a due to uncertainty in average speeds entered into the model and due to uncertainty in driving cyle data underlying the speed correction factor.[25] In doing so, they retained the same functional form for the speed correction ratio, and resampled from the actual emissions to develop estimates of probability distributions for the parameters of the speed correction ratio equation. The probabilistic speed correction factor equation was then used to estimate uncertainty in emissions for average speeds ranging from 2 to 48 mph in 2 mph increments. However, as will be illlustrated later, the functional form of the speed correction ratio may not adequately represent trends in the emissions data. Furthermore, the approach used by Chatterjee *et al.* does not account for uncertainty in the BER.

Since driving cycles are characterized not just by average speed, but by a time variant speed profile, the use of a speed correction ratio is really a form of extrapolation. For example, an average speed can arise from many different driving cycles of various temporal speed/acceleration profiles. To uniquely define a driving cycle would require specification of the actual speed profile or, as an approximation, a joint distribution of speeds and accelerations. Thus, there is uncertainty in the representativeness of a driving cycle even when an "average speed" may be well-known.

Recent activities at the U.S. EPA include the develoment of a variety of segments of driving cycles that can be weighted to represent a variety of different types of trips. The use of weighted averages of driving cycles, rather than extrapolations from driving cycles, is a promising approach for the development of more accurate emissions estimates.

SUMMARY OF TWO RECENT PROJECTS

In the last few years, we have conducted two studies aimed at quantifying variability and uncertainty in highway vehicle emissions. The first is a modeling-based study. The first study, like that of Chatterjee *et al.*, involves re-analysis of the data used to develop the Mobile5a emission factor model. However, the analysis methods differ, as described below.[26] In the second study, we used infrared remote sensing to measure the ratios of CO, HC, and CO_2 in the exhaust plumes of selected types of vehicles, with a focus on school and transit buses.[27] Based upon data regarding vehicle characteristics, including fuel economy, emission factors were developed on a grams per gallon and grams per mile basis. In both projects, intra-vehicle variability and fleet-average uncertainty were estimated. Furthermore, in the remote sensing study, sufficient data were collected on specific vehicles to enable an assessment of intra-vehicle emissions variability. It should be noted that driving cycle and remote sensing data are based upon different measurement methods, and are not directly comparable.

Probabilistic Emission Factors Based Upon Mobile5a Datasets

Estimates of emissions from highway mobile sources are typically developed using a deterministic point-estimate approach. This approach involves the use of emission factor models, such as Mobile5a, to make estimates of vehicle emission factors for HCs, CO, and NO_x. The development of these estimates requires many model input assumptions that are subject to considerable variability and uncertainty. Furthermore, as described above, the model is based upon data sets for which there is substantial inter-vehicle variability. Even for a single vehicle category such as a given technology group of LDGVs, there is substantial inter-vehicle variability in emissions. Typically, the range of measured emissions within a technology group for a given pollutant and driving cycle varied over two or three orders of magnitude from the lowest to the highest value. The variability in individual vehicle zero-mileage BERs estimated using the approach described previously also spans orders-of-magnitude. Thus, the average BER is uncertain due to large inter-vehicle variability and small data sample sizes. Additional uncertainty is introduced by using regression models to predict equivalent FTP Bag 2 emission rates from IM240 data and to predict zero-mileage emission rates from a data set including odometer readings from zero to 50,000 miles. Both regression equations introduce uncertainty in the form of a residual error term. If the functional form of the model fitted to the data is not appropriate, then there is additional uncertainty due to model mis-specification.

Uncertainty in Fleet Average Emissions

A major effort of the project was to quantify the inter-vehicle variability and fleet average uncertainty in emission factors derived from data from specific driving cycles. As a bottoms-up approach to the development of an alternative probabilistic version of Mobile5a, a demonstration model was derived and case studies were carried out.

The demonstration model was derived by characterizing the standard errors of the two regression models used for conversion of IM240 to FTP equivalent values and for characterization of zero mileage emissions and deterioration rate coefficents. A linear model was used by EPA for the latter. However, because the residuals from that model were found to be non-normally distributed, a log-linear model was employed instead. In the log-linear model, the logarithm of the emissions was used as the dependent variable and the mileage level was used as the independent variable. The residuals from the log-linear model are more nearly normally distribution than for EPA's approach and, therefore, are more consistent with the basic conditions required for proper use of least-squares linear regression. The standard errors from the two regression equations enable characterization of uncertainty in the zero-mileage BER.

Because of the limitations of the speed correction ratio previously described, it was decided not to extrapolate between driving cycles. Instead, speed correction ratios were developed only for average speeds corresponding to an actual driving cycle. Thus, no speed correction equation was used. The speed correction ratio was estimated based upon the ratio of a tested vehicle's emissions on a particular cycle divided by that same vehicle's emissions on the Bag 2 portion of the FTP cycle. The inter-vehicle variability in speed correction ratios was used to characterize a sampling distribution for uncertainty in the average speed correction ratio. Uncertainty estimates for the average speed correction ratio were developed for the 10 driving cycles other than FTP Bag 2, ranging in average speed from approximately 2.5 to 65 mph, for the three pollutants and for two technology groups. The technology groups were port-fuel injected (PFI) and throttle body injected (TBI) vehicles equipped with three-way catalysts. A probabilistic simulation package, Analytica, was used to estimate the uncertainty in the average emissions for a given driving cycle, pollutant, and technology group based upon the combined effect of uncertainties in the regression model error terms for the BER, mileage accumulation, and driving cycle-specific speed correction ratio.

The results of one case study are shown in Figure 1 for uncertainty in average NO_x emissions for PFI, three-way catalyst equipped LDGVs for 11 driving cycles. The vertical Tukey bars in the figure depict the 5th, 25th, 50th, 75th, and 95th percentiles of the uncertainty estimates. The comparable point-estimates based upon the Mobile5a model are also shown. These point estimates were obtained by using the technology-specific BER and speed correction ratio equations. Because the output from Mobile5a is averaged over 13 technology groups, these point-estimate results cannot be reproduced merely by running Mobile5a.

The results in Figure 1 are typical of those for other pollutants and for the other technology group evaluated. For example, the results indicate that several driving cycles, such as LSP1, LSP2, LSP3, and NYCC, have similar average emissions. In contrast, the point estimates from the Mobile5a model indicate that emissions are sensitive to the range of average speeds for these four cycles. The probabilistic results indicate that the emissions trends assumed in the speed correction ratio model may not be supported by the emissions data. For example, as average speed increases from 12 to 36 mph, NO_x emissions reported by the model increase, whereas the mean values from the probabilistic analysis tend to decrease. The relative range of uncertainty in the NO_x emissions varies from plus or minus 25 to over 50 percent for a 90 percent probability range, depending on the driving cycle. The differences between the mean values of the probabilistic estimates and the point estimates from the model imply a bias in the model's predictions.

For all of the cases considered, the results indicate that the uncertainty in the mean CO and HC emissions, based on a 90 percent probability range, is approximately 20 to 40 percent. Similar to the results for NO_x, biases were found between the mean values estimated from re-analysis of the emissions data sets and the point estimates obtained from the Mobile5a equations for BER and speed correction ratio.

The reasons for the biases are difficult to explain in some cases because there is limited documentation available regarding how the regression and speed correction ratio equations were developed. One factor that may be important is that improper use of regression analysis techniques can lead to incorrect estimates of mean values. A second factor is that the equation used for the speed correction ratio appears not to be universally valid for all technology groups and pollutants.

Development of Area-Wide Emissions Estimates

The driving cycles underlying Mobile5a are complete trip-based speed profiles. However, no individual cycle may adequately represent area-wide emissions for a typical geographic region.

To address the need for more representative uses of driving cycle data, a probabilistic analysis of driving cycle emissions was carried out using Monte Carlo simulation. To better predict area-wide emissions, a new methodology was presented by which data from multiple trip-based driving cycles can be combined to represent any arbitrary frequency distribution for speed. This method can be applied to the standard driving cycles used in the vehicle testing programs by EPA to better simulate on-road driving patterns and represent observed variations in speeds. Two case studies for vehicles on I-40 were done to demonstrate the working of this new methodology. The methodology can be extended to consider other factors affecting emissions, such as acceleration. However, currently, most routinely deployed traffic detection devices are not capable of recording such information. The development of mixtures of driving cycles is described elsewhere.[28]

On-Road Emissions Estimates for Buses

Remote sensing has been used primarily to help improve inspection and maintenance programs. Remote sensing can be used to obtain instantaneous measurements of tailpipe emissions from on-road vehicles.[29] An infrared beam is sent from a source to a receiver across a road, with a beam height approximately at the level of the vehicle tailpipe. Based upon the transmittance of an infrared (IR) beam within specific ranges of wavelengths, remote sensing devices (RSDs) are able to infer the relative concentrations of CO_2, CO, and HC within approximately a two second sampling period. The first several tenths of a second of the sampling period may be used to collect background information before a vehicle breaks the beam. Measurements of the vehicle exhaust plume may be collected for typically 0.6 seconds. Because of the short sampling time, it is possible to collect data on potentially thousands of vehicles per day using a single RSD. The emissions ratios can be used, in combination with a combustion mass balance model, fuel properties such as composition and density, and vehicle fuel economy, to estimate emissions of CO and HC on a grams per gallon of fuel consumed or grams per mile of vehicle travel basis.

The objectives of this project were to: (1) conduct on-road remote sensing of carbon monoxide (CO) and hydrocarbon (HC) pollutant emissions from selected types of vehicles (i.e. school and transit buses); and (2) determine the on-road emission rates of such vehicles. A total of 1,340 valid remote sensing measurements of on-road emissions ratios of CO/CO_2 and HC/CO_2 were obtained for 265 diesel-fueled school buses, 36 gasoline-fueled school buses, 19 diesel-fueled transit buses of the Triangle Transit Authority (TTA), 3 gasoline-fueled buses of TTA, and 12 diesel-fueled transit buses used as courtesy buses at Raleigh-Durham International Airport (RDU) over the course of 22 days of field work. The development of databases based upon the observed ratios of CO/CO_2 and HC/CO_2 and available information regarding characteristics of the observed buses involved detailed review of both data and video records from the RSD, as well as interactions with several agencies. Numerous quality assurance checks were performed on the data sets, which were analyzed by three different people and reviewed several times for validity. The details of the study are given by Frey and Eichenberger.[27]

As an example of the results, the variability in individual estimated gram per gallon CO emission factors for diesel school buses measurements at one site is shown in Figure 2. Also shown is the mean value and the 95 percent confidence interval for the mean. Diesel school bus data were collected at five different sites. However, it was not possible to identify statistically significant differences in average emissions among the five sites, even though average speeds varied from approximately 15 to 45 mph from one site to another. For some sites, very few data points were collected, leading to wide confidence intervals on the average emissions estimates.

The diesel school bus data were analyzed to attempt to identify explanatory variables for differences in emissions. No statistically significant findings were obtained. This is because the variability in emissions for individual buses was typically similar to the variability in emissions for the entire fleet. Therefore, factors such as vehicle age, odometer reading, vehicle size, manufacturer, and fuel economy were found to be statistically insignificant in explaining variability in emissions. The uncertainty in the average emission factor for diesel school buses is approximately plus or minus nine percent. Thus, although the inter-vehicle and intra-vehicle variability is relatively large, the uncertainty in the fleet average emission factor is relatively small due to the large sample size. In contrast, the uncertainty in the average CO emission factor for gasoline-fueled buses, for which there werely only 88 observations, was found to be plus or minus 17 percent.

The uncertainty in average gram per mile emission factors was found to be due primarily to variability in the remote sensing measurements. The variation in inter-vehicle fuel economy, although spanning a factor of two from lowest to highest value, does not contribute substantially to overall uncertainty. Variations in fuel properties are sufficiently small as to be a negligible contributor to uncertainty in the emission factors, since not all aspects of a complete driving cycle were characterized.

Emission factors calculated based upon remote sensing are specific to the fleets and locations for which data were obtained. In the case of diesel school buses, we obtained a reasonably representative sample of vehicles, based upon considering the variations in vehicle age, odometer reading, manufacturer, and size among the observed vehicles. Because similar measurements were obtained at five different sites, it appears that these emission factors may be representative of at least portions of a typical school bus trip. However, there is additional unquantified uncertainty regarding the representativeness of these emission factors for the purposes of developing emissions inventories.

The data collected from courtesy buses at RDU airport was in some ways the most interesting. This is because data were collected at one site through which all of the parking courtesy buses must drive between Terminals C and A of the airport. Thus, over the course of a working day, the same bus with the same driver could be observed as many as 25 times, enabling repeated measurements over nearly completely controlled conditions, with a primary exception of some variation in passenger load. A key observation from these data was that the intra-vehicle variability in repeated measurements for a given bus was comparable to the overall variability in all of the measurements, which ranged from approximately 3.0 to 30 g/mile for CO. For the three buses for which 25 or more data points were obtained, the uncertainty in the average emission factor was approximately plus or minus 13 to 23 percent. Although we had hypothesized that the orders-of-magnitude variation in emissions measurements were due at least in part to the short sampling time of only 0.6 seconds, these results appear to be consistent with the findings of Bishop *et al.* that substantial variability in repeated measurements is found regardless of the measurement technique used.[18]

One of the original objectives of the study was to identify the fraction of high emitting vehicles in the fleet. However, it is difficult to provide a quantitative answer in response to this objective. Commonly, remote sensing measurements are misinterpreted to indicate the fraction of vehicles that are high emitters. In fact, the distributions of emissions merely indicate that a fraction of the observations occurred during a time period in which a vehicle was producing high emissions. The study of emissions of individual school buses and of individual RDU transit buses illustrates that even individual vehicles can produce a wide range of emissions readings. Therefore, it is difficult to classify an individual vehicle as a high emitter based upon one remote sensing emission measurement of that vehicle.

For the hydrocarbon emissions, the reporting of results is complicated by the fact that remote sensing produces a biased under-estimate of total tailpipe emissions. Thus, we have chosen not to include those results here. We refer the reader to Stephens *et al.* (1996) and Frey and Eichenberger (1997) for more detail on this topic.[27,30]

DISCUSSION AND CONCLUSIONS

The results described here provide insight into random error contributing to uncertainty in fleet average emission factors. For both the driving cycle and remote sensing data, substantial variability in emissions among individual vehicles is evident. The inter-vehicle variability leads to uncertainty in the fleet average emission factor. Based upon the studies reported here, it appears that the uncertainty in average emissions is often plus or minus 20 percent or more. For the driving cycle data, methodological issues regarding regression analysis and specification of the functional form of the speed correction ratio used in Mobile5a were identified as possible sources of bias in highway vehicle emission factors. The assessments of random error are predicated on having a representative, random sample of data. From the remote sensing measurements, it is apparent that repeated measurements of individual vehicles have as much or nearly as much variability as a set of measurements obtained from different vehicles. This latter finding suggests that some variability in vehicle emissions measurement may be irreducible in practice.

Additional sources of uncertainty may include lack of precision and accuracy of the measurement methods and collection of a non-representative or non-random sample of data. Biases due to measurement errors can, in some cases, be relatively easy to identify and correct. Biases due to nonrepresentativeness can be more difficult to quantify.

Emission factors are just one input to an emission inventory. Activity data, such as gallons of fuel consumption or vehicle-miles of travel in a given area over a given time frame, may also be subject to uncertainty. For example, it may be difficult to predict precisely the vehicle count or vehicle miles of travel on a given roadway for a given hour of a given future day when evaluating the effectiveness of proposed control strategies.

In this paper, we have focused on the use of data analysis and conventional statistical techniques for quantification of uncertainty. The use of such techniques requires judgment.[16] Furthermore, in some cases there may be little or no data from which to make estimates of uncertainty even in situations were uncertainty is known or believed to exist. In addition, correction for possible biases may require the use of judgment. Formal elicitation protocols exist for the encoding of subjective probability distributions based upon expert judgment. These methods have been used in a variety of environmental assessments, and are recommended for consideration in the development of emission inventories.[31,32]

Quantification of uncertainty in both emission factors and activity data will enable estimation of overall uncertainty in the total emission inventory. Uncertainties in emission inventories can be propagated through AQMs to determine their effect on predictions of peak ambient pollutant levels. While uncertainty analysis of air quality models has in the past been a daunting task, preliminary efforts to propagate uncertainties have been conducted, such as by Steve Hanna (now with the Harvard School of Public Health), with models as large as the Urban Airshed Model. If the resulting uncertainty in estimated peak pollutant levels leads to ambiguity regarding emissions control decisions, then efforts to reduce uncertainty in the emission inventory can be targeted to improve the decision making process. Using statistical methods such as correlation coefficients or regression analysis, it is possible to identify the inputs to an emission inventory that contribute most to uncertainty in overall emissions. For the most sensitive model inputs, assessments can be made of the "value of information"; that is, the costs of collecting additional data to reduce uncertainty can be weighed against the possible benefits of uncertainty reduction in terms of less ambiguous inventories and more precise predictions of control requirements.

Quantification of uncertainty is the first step toward an improved process for managing resources to reduce uncertainty in emissions inventories and improvements in decision-making processes that depend upon the inventories. Furthermore, efforts to quantify uncertainties often motivate formulation of critical questions regarding: the purpose of an assessment; the specific needs for emissions estimates regarding considerations such as averaging times, geographic area, and dependence with other uncertain quantities; and identification of the most significant sources of uncertainty. All of these activities will lead to a better understanding and use of emission factors and emission inventories. A simple way to begin this process is to start by systematically reporting: the precision and accuracy of measurement methods; mean, standard deviation, and sample size of emissions measurements; the types of averaging implicit in the emissions measurements (e.g., one trip, 0.6 seconds); uncertainty estimates for the mean; and comparisons with other datasets to evaluate representativeness and applicability. The reporting of uncertainty is considered good practice in natural sciences such as physics. It should also be required in environmental science and engineering.

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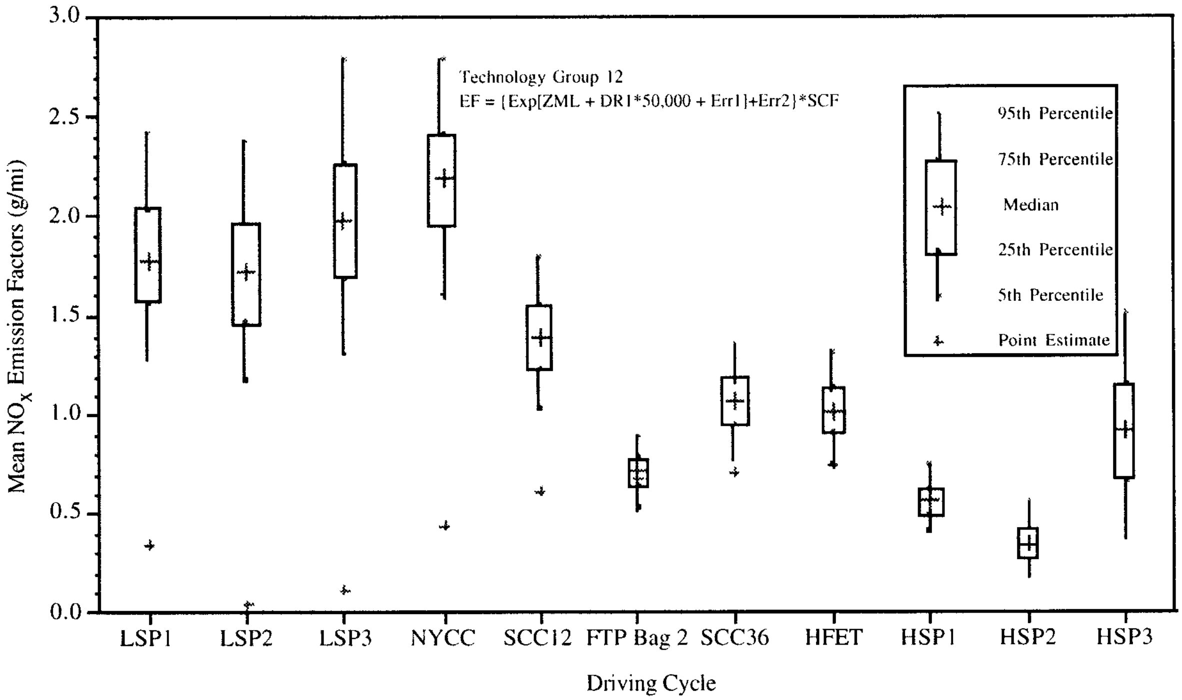

Figure 1. Predicted Uncertainty in the Mean NO_x Emission Factors for Different Driving Cycles for Light Duty Gasoline Vehicles of Technology Group 12 (Port-Fuel Injected, Three-Way Catalyst).

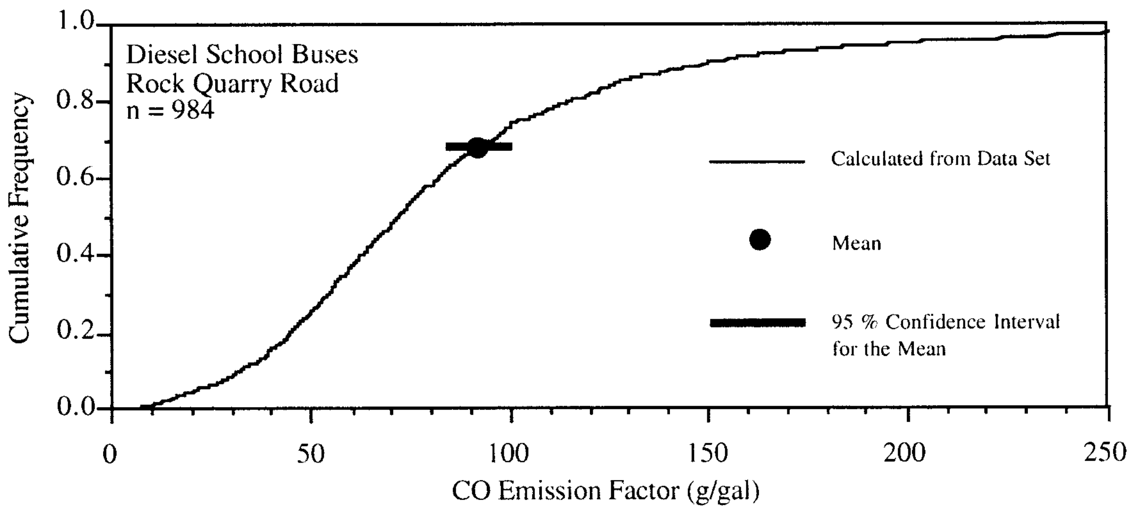

Figure 2. Variability and Uncertainty in 984 Estimates of Diesel School Bus CO Emissions (grams/gallon) based Upon Remote Sensing Measurements at the Rock Quarry Road Site.

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