MODELING AIR QUALITY FOR CONFORMITY, CURRENT DEFICIENCIES AND NEW DIRECTIONS

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ABSTRACT

On November 24, 1993, the US Environmental Protection Agency adopted the transportation conformity rule, pursuant to Section 176(c)(4) of the Clean Air Act. The conformity rule requires that transportation plans, programs and projects funded or approved by the federal government or their agents under Title 23 (Highways) U.S.C. or the Federal Transit Act conform with state or Federal air quality implementation plans. Federal transportation planning regulations contain reciprocal language (40 CFR 450.312(d)), stipulating that the MPO shall not approve any plan or program that does not conform to the SIP as determined in accordance with the conformity rule.

The final transportation/air quality conformity rule (23 CFR Part 450 and 49 CFR Part 613) constrains the development of transportation plans, improvement programs and projects and has increased pressure on statewide metropolitan transportation agencies to ensure that transportation and air quality plans are coordinated. Rigorous requirements for regional and local air quality modeling of transportation systems are included in the final conformity rule, and agencies are working diligently to meet these demands.

The research community and practitioners alike have raised significant questions as to the reasonableness and accuracy for requiring specific modeling procedures--large uncertainties in the modeling process are prevalent. These inherent uncertainties are likely to lead to erroneous transportation planning decisions, and possible mis-allocation of local, state, and federal moneys.

This paper briefly addresses and identifies some of the more significant uncertainty issues associated with the transportation modeling process in context of the demands set forth by the Conformity Rule. The uncertainties listed are not meant to be comprehensive, but instead aims to shed light on the 'missing communication link' between technical experts and policy makers. Modeling requirements and procedures set forth in the Conformity Rule do not reflect the magnitude and depth of current modeling deficiencies.

Solutions to these modeling uncertainties can be provided with advancements in both transportation activity and emissions modeling procedures. It is important for future modeling revisions and upgrades to explicitly include estimates of uncertainty in computations, so that decisions makers can re-shape existing policies--making them more sensitive to explicit uncertainties.

INTRODUCTION

The Transportation Conformity Final Rule (the Rule) [DOT, 1993] lays out specific and detailed modeling requirements that mandate transportation and air quality planners to follow 'laundry list' type procedures. While providing a compelling reminder that urban air quality is a serious problem that needs addressing, the Rule does not reflect the uncertainty recognized by transportation and air quality planners and researchers.

Two important purposes of conformity are to ensure 1) transportation plans will help to eliminate or reduce the severity and number of violations of the National Ambient Air Quality Standards (NAAQS), and 2) transportation activities will not cause or contribute to new violations in any area, nor delay attainment (i.e. increase emissions) of any standard or required interim emission reduction or other milestone in any area [CAA §176(c)(1)(B)]. At this time, conformity applies only to non-attainment areas.

There are basically two levels of analysis with regard to modeling emissions in a given non-attainment area, regional and local. Regional analysis requires estimation of emission inventories from motor vehicles (as well as other sources), while local analysis requires air quality impact analysis for emission 'hot spots'. There is a growing body of research identifying and quantifying the uncertainties associated with current transportation-air quality modeling practice, and a growing concern that poor decisions may be made based on currently mandated modeling techniques [Ismart, 1991; Ireson, Austin, and Carr, 1993; Harvey and Deakin, 1993; Guensler and Geraghty, 1991].

This paper briefly discusses and illustrates some of the major problems associated with modeling emissions from motor vehicles as guided by the Rule. An effort is made to illustrate the nature of the uncertainties involved, as well as to identify

how these errors are likely to affect transportation-air quality analysis results.

CURRENT MODELING DEFICIENCIES

The EMFAC and MOBILE series of emissions models have served very important and critical needs in historical emissions analysis practice. Without these models, the transportation-air quality planning community would lack the tools in which to compare alternative transportation projects or to quantify the emissions impacts of projects. Furthermore, transportation planners would lack the tools necessary to meet the requirements of Clean Air and Transportation Planning legislation.

These models, however, are less than optimal for current emission inventory analysis demands. The ad-hoc development of the models brought about by the dynamic political climate and continually changing air quality analysis needs has left the current analysis models poorly suited to assess the new gamut of proposed transportation projects; transportation demand management strategies, market-based solutions, and intelligent transportation technologies.

We must also acknowledge the role that transportation activity models play in current modeling shortfalls. The accuracy of results provided by emissions analyses depend entirely upon the accuracy embedded in, and provided by transportation activity models. When we consider the joint inaccuracies of transportation activity and emissions models, the results suffer from both biases and inaccuracies of sometimes unknown magnitude and direction.

The current emission modeling deficiencies are categorized as follows: 1) link between Urban Transportation Planning system (UTPS) type models and emission models; 2) methodological errors; 3) sampling errors; and 4) model validation problems.

Link Between UTPS and Emission Models

As stated previously, the link between transportation activity models (UTPS type models) and emissions models is of critical importance for accurate emissions analyses. In fact, the accuracy provided by emissions models is largely a function of the accuracy provided by activity models. In this section, three general areas of inaccuracy and precision are discussed.

Level of detail provided by UTPS models

Many contemporary proposed transportation solutions do not intend to increase transportation supply. In fact, many solutions bring about microscopic flow changes to the transportation system. For example, high occupancy vehicle lanes (HOV) and ramp metering intend to smooth flows on freeways. HOV lanes aim to increase the demand for ride-

sharing, thereby reducing vehicle demand and making the transportation system more efficient. Ramp metering aims to regulate traffic flow onto the freeway so that demand will not exceed capacity. In each of these cases, microscopic flow changes occur, bringing about sometimes subtle yet important changes to vehicle speed time profiles. For example, the number and severity of acceleration and deceleration events will change with ramp metering. Hard accelerations from vehicles leaving the merge lane queue will increase, while high-speed accelerations and decelerations from mainline vehicles will likely decrease. These microscopic flow changes represent important changes in the calculus of emissions, however, they are difficult or impossible to capture with current transportation activity models.

Typical regional transportation activity models (of the UTPS family of models) provide travel activity outputs by transportation system link, time of day (off peak vs. peak), and directional split. Vehicle miles of travel (VMT) is the most common measure given to quantify vehicle activity on the transportation network. The only measure of macroscopic roadway performance provided is mean vehicle speed (by link), while there are no provided measures of microscopic performance. Considering the fact that microscopic flow changes are critical for correctly assessing emission impacts, it is unlikely that changes to average operating speed brought about by transportation projects like the addition of HOV lanes or ramp metering will accurately reflect the emission impacts upon the transportation corridor.

The unfortunate outcome is that the wide variety of transportation projects, many of which may improve air quality, are not being modeled with the accuracy needed to determine their impact on emissions. Specifically, those projects that bring about microscopic changes to the transportation network are at highest risk of being wrongly assessed. Emission impacts cannot be examined at the transportation corridor level.

UTPS model calibration errors

The typical Urban Transportation Planning System (UTPS) process consists of four steps: trip generation, trip distribution, mode choice, and trip assignment. These four steps comprise the mathematical models that ultimately predict transportation activity in a metropolitan region. Although much has been written about the uncertainty of individual steps in this process, the focus in this section--and the perhaps the most significant in terms of emission impacts--is the second of these steps, trip distribution.

Trip distribution models have been widely criticized for some time. There are several types of trip distribution models, including gravity, growth factor, multi-nomial logit, and intervening opportunities models. The most widely used type of trip distribution model today is the gravity model. The gravity model has been criticized for poorly modeling the true

causes of trip making [Williams, 1977], for requiring the use of K factors to arbitrarily adjust the level of tripmaking between locations [Halcrow, Fox, and Associates, 1984; Hutchinson, 1980], for possessing 'grossly inadequate explanatory powers' [Sikdar, Smith, and Hutchinson, 1980]· for containing fixed K factors that are likely unstable over time [Harvey, et al., 1993; Stopher and Meyburg, 1975], and for over-estimating near trips and under-estimating far trips [Dickey, 1983].

The more advanced modeling technique, the multi-nomial logit trip distribution model, is more robust than the gravity model [Harvey, et al., 1993]. This model includes variables that reflect the attractiveness of destination attractiveness, origin-destination travel conditions, and personal characteristics that influence travel decisions [Harvey, et al., 1993]. However, this model requires far more data, and is still used by only several regional agencies, thus, the gravity model is still used in the majority of regional modeling practice [Harvey, et al., 1993].

There are essentially two times in the trip distribution process when link attributes are adjusted so as to compromise the accuracy of link level vehicle activity estimates. The first is in the calibration of the gravity model used for trip distribution. The gravity model is used to distribute traffic volumes around a network and between zones. The gravity model is the most commonly used model in regional modeling and takes the form [Dickey, 1983]:

$T_{ij} = P_i \cdot A_j \cdot F_{k(ij)}$; where,

T_{ij} = number of trips produced in zone i and attracted to zone j,
P_i = number of trips produced by zone i,
A_j = number of trips attracted to zone j,
$F_{k(ij)}$ = travel time factor (friction factor) between zone i and zone j for interval k.

In the gravity model, trip interchanges between zones are inversely proportional to the friction factor, F. This friction factor is usually some surrogate measure of travel cost, thus, increasing travel time between zones decreases the likelihood of travel between zones, and therefore the number of trip interchanges between zones. The Bureau of Public Roads in 1965 proposed a calibration procedure whereby an iterative procedure is used to estimate friction factors between zones. This procedure, being widely used today, begins by assuming certain friction factors and then iterating through so that predicted zonal trip interchanges match the zonal interchanges predicted by the trip generation model. The iterative process ensures that predicted trip productions are equal to actual trip productions, however, trip attractions are usually not reconciled [Dickey, 1983]. To reconcile both trip productions and attractions, an iterative factoring process is utilized until all estimated values match trip generation predicted values. This means that the model will over-

estimate trips on some links, while under-estimating trips on other links.

To 'correct' problems with trip distribution tables, UTPS models are calibrated to 'agree' with field data. During this calibration process, individual link attributes (trip speed, trip length, etc.) can be adjusted so that modeled volumes are equal to observed ground counts. For example, an FHWA regional modeling calibration manual suggests shortening or lengthening trip times in order to make routes more or less attractive [Ismart, 1990].

Let us reiterate the necessity for the calibration process. What is happening internal to the model algorithms is that statistical models are not capturing a large portion of the variation in trip making behavior between individuals in different geographical locations. This is due to several factors. Data aggregation by zone forces 'like' people within zones to make trips in a similar manner. For example, a model might predict that a 4 person household (2 young children) living in a similar neighborhood with similar household income will make the same total number of trips per day. Because it is hard to incorporate variables that are important for trip making behavior, such as stage in one's life cycle [Kitamura, 1988], it is similarly hard to estimate with accuracy differences in trip making between households. This difficulty translates to models where estimated trips are significantly different than observed trips, so, we compensate by adjusting K factors, link speeds, etc.

What these calibration errors mean to emissions estimation are unclear. We can speculate, however, on the impacts of adjusting travel times (either adjusting link speeds or link lengths) on emission estimates. In order to change a travel time, we must either change link distance, or speed of travel. Of course we should never change link distance unless it is to make it correspond to true link distance. By changing link speeds, on the other hand, we will change average operating speed estimates of vehicles.

If ground counts on a link are greater than the model-estimated traffic volumes, the FHWA manual indicates that we must increase travel time on the link. To increase travel time on the link we need to decrease average link speeds. Decreasing link speed is accomplished by "tinkering" with the BPR curve, e.g. reducing the modeled capacity of the segment so that a given traffic volume will be modeled as exhibiting a lower average speed.

The problem is that very few studies are ever conducted to determine whether modified link speeds ever match the link speeds predicted by the model after re-calibration of the BPR curve is undertaken to reconcile traffic volumes.

No matter what we manipulate to reconcile traffic volumes, we will affect estimates of emissions from motor vehicles. The critical issue becomes, then, the magnitude and direction of change necessary to calibrate a 'typical' urbanized region.

For example, suppose a 5 mile two-lane link has an observed a.m. peak period traffic volume of 1800 vehicles per hour per lane, totaling 3600 vehicles for a one hour period. Suppose that our regional model predicts traffic volumes of 4000 vehicles per hour. In order to reduce the flow on the link, we must either increase the travel time on the link or increase the link distance. If we increase the travel time (reduce average speed) on the link to make ground counts match estimated traffic volumes, then we under-estimate the average operating speed, which changes our estimate of emissions on this link.

Treatment of recurrent and non-recurrent delay

Finally, we consider the treatment of non-recurrent congestion. UTPS type models do not have a specific mechanism for modeling the random occurrence of incidents and accidents. Because approximately 60% of observed network delay is non-recurrent and is caused by accidents or incidents, this delay is not typically included in ground count volumes or observed speeds. For example, UTPS modelers compare predicted traffic volumes and average speeds to ground counts and observed average speeds. When recording ground counts and average speeds on a network link, days when traffic is 'gridlocked' due to an overturned truck are not used as an 'average' day for that link, and are discarded. That event represents a random occurrence that contributes to about 60% of the total delay experienced by motor vehicles. In effect, a large portion of the total delay experienced by motorists on a network is not reflected in UTPS modeled outputs, contributing to underestimation of overall emissions.

From a regional perspective, failure to account for the emissions impacts of accident delay may play a role in whether air quality plans are designed to achieve attainment. However, from an analytical perspective, the exclusion of non-recurrent delay is only a problem when transportation - air quality planners want to assess transportation projects or programs that may affect non-recurrent accidents or incidents. As the typical procedure for assessing the emission impacts of a transportation project or program is to model pre and post project emissions, a project or program that reduces non-recurrent congestion will not be shown to be beneficial to air quality. Examples of these projects include: roving emergency vehicle services; advanced warning message signs; in-route vehicle information services; and vehicle safety inspection programs. Although these sorts of transportation projects or programs may be extremely beneficial and cost effective for improving air quality in a region, there is no way to demonstrate this with the currently mandated modeling tools.

Methodological Errors in Emission Models

This section addresses several putative yet onerous errors besetting air quality analyses. The topics are not meant to be exhaustive, but instead focus on areas that raise serious questions as to the uncertainty present in air quality analysis.

Statistical confidence in modeled outputs

One of the problems associated with current emissions models is the absence of error or confidence bounds. Without confidence bounds to provide an indicator of the uncertainty introduced by sampling errors, we have little information in which to construct useful policies surrounding the use of emissions models.

Investigation into the nature of the uncertainty surrounding the speed correction factor curves embedded in the EMFAC model shed light onto the seriousness of this problem [Guensler, 1993]. The research showed that the confidence intervals surrounding the Speed correction factor curve are quite large, and that the uncertainty expressed in the currently employed statistical relation between emissions and average vehicle operating speed is quite large.

The confidence interval concept is extremely important in the context of conformity analyses. Assume that our model predicts a mean emission rate for a specified fleet of vehicles moving at 10 mph average speed is 4 grams per mile. The 95% confidence interval, however, suggests that the mean emission rate for this fleet is actually between 3 and 5 grams per mile. Despite the fact that our model has predicted 4 grams per mile, we are 95% confident that the true mean emission rate, considering the random uncertainty in emission rates, lies between 3 and 5 grams per mile.

It is important to note that the confidence interval issue is not an issue of random error that disappears as the model is applied to numerous applications. Every time the model is asked to provide a mean emission rate for an average speed of x mph, the model will return a value of y grams/mile. Thus, every time the model is applied, it systematically over or under-estimates the emissions associated with this average speed.

If policy makers were provided with confidence interval information, they would better understand the limitations of the current state of the practice emission models and potential implications of their decisions. Continuing from the above example, if a policy required rejection of transportation strategies that resulted in emission increases, we could not be sure that our models predicted higher emission because of randomness, or because of a true increase in emissions. This distinction is important, because you could actually reject a possibly beneficial transportation strategy that showed negative emission impacts because of random uncertainty.

Use of fleet average FTP Bag2 averages

Current emissions models employ fleet average Federal Test Procedure (FTP) 'Bag 2' emission test results. That is, the average emission rate from a fleet of vehicles tested on the FTP Bag 2 test is used as a component of the emissions models. Both regional emissions models, EMFAC in California and MOBILE in the remainder of the US, and

many of the micro-scale, or project level models, use approximated fleet average values. Significant problems arise when fleet average test results are used as inputs to emissions models.

The first is that the models predict the same emission rate for any vehicle on the roadway. The mathematical equations derived for predicting emissions are generally a function of the average measured emission rate and other vehicle activity variables. They typically take the form:

$E_i = f(e_i, a_i, c_i)$;   where,

    E_i = model predicted average emission rate on link i,

    e_i = average FTP Bag 2 emission rate for vehicles on link i,

    a_i = average vehicle activity estimate on link i,

    c_i = average breakdown of vehicle technologies and classes on link i.

The required model inputs are typically average values-- average FTP Bag 2 emission rate for the approximated regional fleet; average vehicle activity, usually average speed by link; and average breakdown of vehicle technology by region. Average vehicle activity is derived from transportation activity models. Average FTP Bag 2 emission rates are derived from various sources: continued regional and statewide emissions certification testing results; estimated emissions degradation from accumulated mileage of existing on road vehicles; and from estimates of the make up of the regional vehicle fleet [USEPA, 1992a; USEPA, 1992b; CARB 1991; CARB, 1992; CARB, 1994].

It is important to note that our goal in emissions modeling is to predict both spatial and temporal dispersion of emissions. Because individual 'dirty' vehicles can contribute significantly to local and regional emission inventories, it is important to identify when and where these dirty vehicles operate. Furthermore, when these high emitting or 'dirty' vehicles engage in aggressive driving behavior, their contribution to the emission inventory can be even more substantial. As long as the models employ fleet average Bag 2 emission rates, we will not be able to effectively assess transportation policies and strategies that target the complex interactions between certain vehicle types and certain vehicle activities.

The second problem with using fleet average FTP Bag 2 emission rates is that small mis-representations of the fleet average by region can result in large mis-calculations of fleet average emission rates. Specifically, the proportion of high emitters has extreme influence on the computation of fleet average values, which in turn will impact estimates of carbon monoxide emissions for a vehicle fleet.

Because both the CALINE4 and EMFAC7F models rely on fleet average FTP Bag 2 emission rates for computational

accuracy. The models require that the estimated Bag 2 average is the 'true' average value for the entire regional fleet. If for example, estimated FTP Bag 2 averages are higher than those in the true fleet, the models would over-estimate carbon monoxide emissions. The concern is, how much over or under estimation will occur from using an incorrect estimate of the fleet average FTP Bag 2 emission rate?

Unfortunately, emission rates are not normally distributed, and only a small portion of the cleanest vehicles exhibit behavior that follows a normal distribution. Using a more subjective criteria to identify outliers, and using a cut-point of 62.13 grams per kilometer (100 grams per mile) to separate normal from high-emitting vehicles, the distribution becomes apparent. This cut-point is chosen because it is an easy to remember cut-point, and because it is not subject to variation in vehicle fleet composition. For example, an identification scheme employing the sample mean and one or two standard deviations from the sample mean is dependent upon the sample, and will vary across test samples, whereas using 62.13 grams per kilometer (100 grams per mile) is a consistent means in which to separate high emitters from normal emitters.

Table 1 shows the breakdown of the high-emitters contained in the Speed correction factor data set for CO. For example, when 7.8% of the vehicles exhibit test result emission rates greater than 62.13 grams per kilometer (100 grams per mile), their contribution to the total emission inventory for that fleet is roughly 72%. Their proportion of a weighted average emission rate from all activity represented by the testing cycles would be 72%. Similarly, 3.5% high emitters in the fleet contribute to 53%, all other things being equal. The table shows that mean emission rates increase disproportionately to corresponding proportions of high-emitting vehicles. For example, increasing the proportion of high emitting vehicles from 3.5% to 7.5% corresponds to an increase in the mean emission rate from roughly 9.9 to 16.2 grams per kilometer (16 to 26 grams per mile). Therefore, small variations in the estimated average FTP Bag 2 emission rate bring about large impacts in emission estimates.

To illustrate the extreme importance of the results provided in Table 1, consider the following example. If we estimate that 3.5% of the vehicle fleet emit over 62.13 grams per kilometer (100 grams per mile), but in reality 7.5% are high-emitters, then we will under-estimate the true mean emission rate by roughly 5.9 grams per kilometer per vehicle (9.5 grams per mile). Applying this mistake on a region wide basis, we could expect an under-estimation of CO emissions by roughly 10 metric tons per million vehicle kilometers of travel, or an under-estimation of the contribution of high-emitter CO pollution to the total emission inventory by about 20%. Of course, the reverse effect would occur if the proportion of high emitters in the vehicle fleet was over-estimated.

Table 1 - Summary of High-Emitter Impact on Emission Inventory

Proportion of Vehicle Test Results above 62.13 grams / kilometer (% High-Emitters)[2]	Mean Emission Rate (grams / kilometer)	Median Emission Rate (grams / kilometer)	Total Emissions Associated with Speed Correction Factor Database Test Vehicle Emission Results (%)
7.85	16.66	1.80	72.27
7.50	16.15	1.79	71.27
6.80	15.10	1.74	69.04
4.63 [1]	11.86	1.68	59.66
3.54	10.29	1.67	52.99
3.15	9.72	1.62	50.06
2.38	8.57	1.62	42.89

[1] Proportion of high-emitters (> 62.13 grams/kilometer) contained in speed correction factor data set for CO (Bag1 and Bag3 vehicles not included)

[2] Percent of high-emitters in fleet was varied by randomly omitting or adding high emitting vehicles to the existing speed correction factor database vehicles

Separation of automobile certification and emission inventory modeling

A fundamental and critical question has thus far not been sufficiently addressed in the emissions model development arena is: Should motor vehicle emission certification issues be separated from emission modeling development, i.e., should certification test results play a useful role in the derivation of modal emission testing protocol as they have in past US model development efforts?

Currently, vehicle certification and emission model development rely upon test results from the current 'certification cycle'. The certification cycles (i.e. the Federal Test Procedure, Highway Fuel Economy Test, and new IM240 and Unified Cycles) were designed to serve as emissions benchmarks, against which vehicle-to-vehicle emissions performance can be compared. In using emission testing cycle data for emission modeling purposes, there is an inherent presumption that if a vehicle operates cleanly on the certification cycle it is likely to operate cleanly under onroad operating conditions. However, separation of vehicle certification from model development may be extremely beneficial.

Vehicle certification and emission model development should be separated. This separation would represent a significant departure from current practice, as existing models have been developed simultaneously with vehicle certification testing cycle development. Separation of vehicle certification testing from emission model development may make technical and practical sense, since emission forecasting and vehicle certification have two distinctly different objectives: vehicle certification is an enforcement tool that aims to ensure that vehicle fleets meet emission standards while driven over a 'typical' driving cycle, whereas emission modeling is a planning tool used to forecast emission inventories and impacts from a fleet of motor vehicles driven over any number of possible cycles. It is not entirely clear that these two objectives are compatible or complimentary. De-coupling contemporary vehicle certification issues from emission modeling issues may allow more effective pursuit of these individual and independent objectives.

Sampling Errors

A problem that has largely not been recognized is the fact that the mathematical algorithms employed in regional emission models (EMFAC and MOBILE) were derived using outdated and statistically non-representative vehicle fleets. The consequence is that the relationship between emission rates and vehicles is not well represented in the models.

To illustrate, consider the distribution of California vehicles shown in Table 2. It depicts the percentage of currently registered California vehicles by model year and inertial weight [Smith, et al., 1995]. Not shown in the table are pre-1977 model year vehicles, which account for approximately 10% of the total road fleet in California. Ideally, an emission model that defines the relation between emission rates and vehicles should be derived using a representative sample of vehicles from the on-road fleet, with the range of vehicle technologies, weights, and engine types represented. Of course, the primary objective is to obtain representative emission characteristics of on-road vehicles. Model year and

inertial weight classifications, shown in Table 2, are reasonably 'good' indicators of emissions. Model year is a 'surrogate' variable that partially captures the effect of technological penetrations of fuel delivery technology, evaporative emissions control equipment, catalytic converter equipment, engine technology improvements, and engine degradation characteristics. Inertial weight, on the other hand, partially captures the effect of load, engine size, number of cylinders, engine power, and engine torque [Smith et al, 1995]. Other useful classifications might include fuel delivery technology and horsepower to weight ratio.

Table 2 - Percent of California Registered Automobiles by Model Year and Inertial Weight

Model Year	DMV DATA Percent Autos Registered	EPA DATA Vehicle Inertia Weight										Row Sum
		1750	2000	2250	2500	2750	3000	3500	4000	4500	5000	
1977	2.12%	0.00%	0.03%	0.16%	0.09%	0.07%	0.11%	0.14%	0.62%	0.66%	0.25%	2.12%
1978	2.69%	0.00%	0.06%	0.21%	0.19%	0.12%	0.22%	0.72%	0.54%	0.48%	0.15%	2.70%
1979	2.81%	0.00%	0.06%	0.18%	0.28%	0.12%	0.33%	0.70%	0.69%	0.40%	0.06%	2.82%
1980	2.76%	0.00%	0.08%	0.34%	0.34%	0.28%	0.59%	0.63%	0.38%	0.10%	0.00%	2.76%
1981	3.09%	0.00%	0.07%	0.42%	0.54%	0.25%	0.57%	0.65%	0.46%	0.11%	0.00%	3.08%
1982	3.36%	0.00%	0.07%	0.38%	0.62%	0.41%	0.67%	0.61%	0.52%	0.08%	0.00%	3.36%
1983	4.51%	0.00%	0.05%	0.56%	0.70%	0.49%	0.85%	0.94%	0.82%	0.10%	0.00%	4.51%
1984	5.55%	0.00%	0.05%	0.47%	0.79%	1.07%	1.04%	1.16%	0.88%	0.09%	0.00%	5.55%
1985	6.59%	0.02%	0.04%	0.51%	1.03%	1.15%	1.25%	1.50%	1.02%	0.07%	0.00%	6.59%
1986	7.40%	0.05%	0.04%	0.50%	1.09%	1.27%	1.90%	1.86%	0.61%	0.07%	0.00%	7.40%
1987	7.14%	0.03%	0.07%	0.31%	1.31%	1.26%	1.83%	1.68%	0.61%	0.05%	0.00%	7.15%
1988	7.70%	0.04%	0.13%	0.29%	1.30%	1.09%	2.26%	1.93%	0.59%	0.01%	0.00%	7.63%
1989	8.10%	0.02%	0.11%	0.23%	1.08%	0.97%	2.76%	2.17%	0.70%	0.07%	0.00%	8.11%
1990	8.10%	0.01%	0.06%	0.09%	0.87%	0.99%	2.62%	2.48%	0.93%	0.06%	0.00%	8.11%
1991	7.62%	0.00%	0.13%	0.11%	0.67%	1.30%	2.44%	1.91%	0.99%	0.06%	0.00%	7.62%
1992	9.02%	0.01%	0.16%	0.14%	0.63%	1.41%	2.35%	2.90%	1.29%	0.12%	0.02%	9.03%
1993	11.43%	0.01%	0.18%	0.17%	0.84%	1.68%	3.05%	3.60%	1.74%	0.15%	0.02%	11.45%
Column Sum	100.00%	0.19%	1.41%	5.07%	12.37%	13.94%	24.85%	25.58%	13.41%	2.68%	0.49%	100.00%

Source: California Department of Motor Vehicles and United States Environmental Protection Agency
0.00% is < 0.01%

To illustrate the importance of obtaining a representative fleet of vehicles, consider the distribution of California vehicles shown in Table 2. We see that 3500 lb. 1993 model year vehicles represent a relatively large fraction of the California vehicle fleet. We must be sure that this 'class' of vehicles is well represented in the test fleet or we may miss important emission characteristics from this 'class' of vehicles.

Table 3 shows the percent of California vehicles contained in the Speed correction factor (SCF) database used to estimate the current EMFAC and MOBILE emission models. From inspection we see that there are no vehicles beyond 1991 contained in the data set. We also see that very few light or heavy vehicles are represented in the data set. Casual inspection of Table 3 shows that the true distribution of California vehicles is not approximated well by the collection of vehicles used to derive the critical emission rate formulas contained in the EMFAC emissions model.

The problem of non-representativeness can only be solved through procurement and testing of an updated and representative set of on-road vehicles. It should also be recognized that vehicle fleets can change significantly across regions and states, and that these differences should be explicitly accounted for in any model improvement effort.

Model Validation Problems

There have been many research efforts to validate (or invalidate) the results of emissions models. This section discusses three of these validation efforts: tunnel studies; remote sensing studies; and ambient air quality studies.

Tunnel Studies (Adapted from Washington, 1994)

Tunnels are a natural test site in which to measure emissions from a fleet of vehicles because ambient air exchanges are minimized by the impermeable tunnel walls, traffic flows can be measured fairly accurately, and air quality monitors can be strategically placed to measure emissions from the fleet of vehicles passing through the tunnels. In theory, observed concentrations of pollutants in the tunnels can be compared with model-predicted concentrations.

Several tunnel studies have been conducted to compare predicted and observed emissions. Most efforts thus far have compared the observed ratio of pollutant concentrations with the predicted ratio

Table 3 - Percent of California Automobiles by Model Year and Inertial Weight Contained in the Speed Correction Factor Data Base

Model Year	1750	2000	2250	2500	2750	3000	3500	4000	4500	5000	Row Sum
					Vehicle Weight						
1977					0.48%	0.16%	0.32%	1.27%	0.95%	1.43%	4.60%
1978		0.16%	0.48%	0.32%	0.32%	0.95%	1.27%	0.79%	1.43%	0.63%	6.35%
1979											0.00%
1980				0.16%			0.16%				0.32%
1981		0.48%	3.65%	4.44%	0.95%	7.78%	2.86%	4.60%	1.11%		25.87%
1982					1.75%	1.43%	0.63%	0.63%	0.16%		4.60%
1983		0.16%	0.48%	1.11%	1.75%	5.56%	0.63%	2.06%			11.75%
1984					1.59%	3.65%	3.65%	0.95%			9.84%
1985	0.16%		0.48%	1.11%	1.75%	3.97%	1.90%	0.63%			10.00%
1986			0.32%	0.16%	0.95%	2.86%	0.79%	0.32%			5.40%
1987			0.16%	0.32%	2.38%	3.02%	2.86%	0.79%			9.52%
1988			0.16%	0.16%	0.63%	2.38%	1.75%	0.79%			5.87%
1989				0.48%	0.48%	3.49%	0.95%	0.32%			5.71%
1990							0.16%				0.16%
1991											0.00%
1992											0.00%
1993											0.00%
Column Sum	0.16%	0.79%	5.71%	8.25%	13.02%	35.24%	17.94%	13.17%	3.65%	2.06%	100.00%

of pollutant emissions based upon outputs from predictive models such as the CARB's EMFAC and the USEPA's MOBILE models. The calculated average emission rates in tunnel studies (based upon observed pollutant concentrations, measured airflows, and observed vehicle activity) are compared with the emission rate outputs from predictive models such as the CARB's EMFAC and the USEPA's MOBILE models. Although the fruits of this research are extremely valuable, little has been done to investigate whether tunnel studies reflect a 'representative' sample of driving behavior and vehicle fleet characteristics for which modeled emissions should be compared. Furthermore, the implications of using such tunnel studies to validate or invalidate current models have not been assessed.

There are three tunnel studies which provide data on CO, HC, and NOx emission rates, and CO/NOx and HC/NOx ratios (earlier tunnel studies are omitted because of non-representativeness of the vehicle fleets and because of the use of EMFAC 7C for emission estimation during those studies). The three studies represent data from the Van Nuys (Sherman Way) Tunnel [Ingals, 1989; Pierson, Gertler, and Bradow,

1990] in Los Angeles, California, the Fort McHenry Tunnel [Gertler, Pierson, Zeilinska, Robinson, and Sagebiel, 1993] located in Baltimore, Maryland, and the Tuscarora Mountain Tunnel [Gertler et al., 1993] located in Pennsylvania. The Van Nuys tunnel is about 222 meters long, has a maximum grade of about 1.7%, and contains 3 lanes both eastbound and westbound. The Fort McHenry Tunnel is 2,174 meters long, has a maximum grade of about 3.76%, and has four bores. The Tuscarora Tunnel is 1,623 meters long, has a maximum grade of about 0.30%, and has 2 bores. Both the Van Nuys and Tuscarora Tunnels contain horizontal curvatures. The emissions data from the Van Nuys, Fort McHenry, and Tuscarora Tunnels were collected in October and December of 1987, June of 1992, and September of 1992 respectively.

In the Van Nuys Tunnel study, gram per mile emissions of CO, NOx, and HC, and emission rate ratios of CO/NOx and HC/NOx were compared to EMFAC7C predicted emission rate ratios [Pierson et al. 1990]. Table 4 below summarizes the results from the study.

Table 4- Summary of Emission Results from Van Nuys Tunnel Study[$]

result (result standard deviation)	CO (grams / mile)	HC (grams / mile)	NOx (grams / mile)	CO / HC / NOx (NOx⇒1)
2 Low Speed Runs (13 mi/hr[*])				
Measured	40.8 (4.6)	5.0 (4.6)	1.26 (0.15)	32.5/4.0/1
EMFAC7C Predicted	33.6 (1.8)	2.72 (4.6)	1.95 (0.13)	17.3/1.4/1
19 High Speed Runs (14 mi/hr[*])				
Measured	21.0 (5.2)	2.7 (1.2)	1.59 (0.35)	13.3/1.7/1
EMFAC7C Predicted	7.5 (1.0)	0.65 (0.07)	1.44 (0.15)	5.3/0.45/1

[$] Adapted from Pierson, et al. 1990.
[*] Average of run-median speeds.

Assessment of the Van Nuys Tunnel Study led researchers to make the following conclusions [Pierson et al. 1990]: the Van Nuys Tunnel Study results agree with other on-road experiments done around the US, which support the notion that emission rates of CO and HC as well as emission ratios of CO/NOx and HC/NOx are higher than dynamometer model predictions; "The discrepancy between the CO/NOx emission rate ratio from the Van Nuys tunnel and the predicted CO/NOx emission rate ratio is a factor of about 2.2, comparable with the 1.8-fold discrepancy between ambient CO/NOx concentration ratios and emissions inventory CO/NOx ratios"; and that some contributing factors to the shortfall in HC and CO estimates are inadequate treatment of running evaporative losses, the effect of mal-maintained and tampered vehicles in the fleet, and the lack of vehicle modal activity reflected in the tunnel. Note, these conclusions assume that the model predictions for NOx are correct: if NOx emissions are under-predicted, the HC and CO emission predictions are under-predicted even more significantly than indicated; if NOx emissions are over-predicted, the HC and CO emission predictions are not as significantly under-predicted as indicated.

The Tuscarora and Fort McHenry Tunnel Studies, however, revealed good agreement between measured emissions and modeled emissions from the USEPA's mobile source emission model, MOBILE 4.1. Table 5 shows the results from the study.

Table 5- Summary of Emission Results from Tuscarora and Fort McHenry Tunnel Study[5]

result (result standard deviation)	CO (grams / mile)	HC (grams / mile)	NOx (grams / mile)	CO / HC / NOx (NOx$\Rightarrow$1)
Tuscarora Runs [*]				
Measured	4.89 (0.49)	0.29 (0.06)	0.39 (0.26)	12.5/0.74/1
MOBILE 4.1 Predicted	7.06 (0.55)	0.45 (0.02)	0.64 (0.07)	11.0/0.70/1
Fort McHenry Runs [*]				
Measured	6.44 (0.63)		0.67 (0.16)	9.6/na/1
MOBILE 4.1 Predicted	3.85 (0.56)		0.57 (0.07)	6.75/na/1

[5] Adapted from Gertler, et al. 1993.
[*] Arithmetic Average of runs - Light Duty Vehicles.

The table shows that in most cases, MOBILE 4.1 over-predicts emissions measured in the tunnels. The authors concluded that: "Mobile source emission factors can be measured in tunnels"; "Tunnels can be used to test and determine deficiencies in emission factor models"; "High emitters may have a major impact on total emissions"; and "Grade has a significant (factor of 2) impact on CO and NOx emissions" [Gertler et al. 1993]. However, tunnel studies cannot be used to pinpoint the flaws in modeling methodology.

In reviewing the results of the tunnel studies (and other tunnel studies yielding similar results), several key issues have not been sufficiently addressed. Does agreement of tunnel studies with emission model estimates provide sufficient evidence to 'validate' the emission models? In other words, is there evidence to suggest that the tunnel studies, when performed correctly, provide realistic estimates of emissions from motor vehicles under 'normal' or 'average' driving conditions? The general answer is 'sort of.' The driving behavior in tunnels is likely to be very different than 'normal' driving behavior. Considering that a very small percentage of the time is spent driving in tunnels, where driver behavior may be much more conservative than normal , one can question the representativeness of vehicle activity in tunnels.

Is this unique driving situation the best 'test' for the emission models, or does it introduce some bias? To answer this question, we must look briefly at the methodologies employed in the current emission models.

The speed correction factor methodologies employed in current emission models employ the results of dynamometer tests under different average operating speeds to establish 'speed correction factor curves' which are assumed to represent driving behavior. In essence, to estimate the emissions in a tunnel where the average speed is 45 mph, for example, the statistically derived ratio of emissions results for vehicle tests at 45 mph average speed and emission results for vehicle tests at 16 mph average speed define the EMFAC speed correction factor [Guensler, 1993]. The 16 mph average speed cycle (FTP Bag 2) employs a variable cycle, containing many modes of operation (acceleration, deceleration, cruise, and idle events). As will be discussed later, increased modal activity leads to increased emissions. The amount of modal activity is generally quite different across test cycles, where the high-speed cycles used in the SCF derivation methodology (which were derived from a relatively stable portion of the highway fuel economy test) exhibit significantly less variation. The derived speed correction factor is dependent upon the ratio of emission

under these two distinctly different cycles with different emission profiles. This ratio, in the case of our hypothetical tunnel study for an average speed of 45 mph, is applied to baseline emission rates for the fleet of vehicles entering the tunnel (FTP Bag 2 test results).

Two factors become critical in the appropriateness of the SCF used in the tunnel studies. First, the speed correction factors were derived through flawed statistical methods [Guensler, 1993] and the SCFs used in the tunnel studies were unlikely to be representative of the conditions to which they would normally be applicable (i.e., if the vehicles were driven in the same modal patterns under which they were tested to gather the SCF data). Second, the speed correction factor generated from testing cycle activity near an average speed of 45 mph is not likely to be appropriate for the tunnel activity to which it is applied. If the driving behavior in the tunnels is less variable than the modeled cycle, then the model is likely to over-estimate emissions. If the tunnel driving activity contains more modal activity than the emission testing cycle, then the model is likely to underestimate emissions.

Remote Sensing

Remote sensing and laboratory studies indicate that the underestimation of emissions is likely due to both unaccounted high-emitting vehicles in the vehicle fleet and unaccounted 'off cycle' emissions excluded from the FTP and SCF testing cycles. Chase car studies and instrumented vehicle studies have confirmed the presence of a large amount of 'off cycle' emissions, and have indicated that present cycles need revision [Carlock, 1991; LeBlanc, et al., 1994].

However, we must be concerned with the implications of remote sensing studies with regard to identification of high-emitters. A plot of observations of high-emitting remote-sensed vehicles against the same vehicles tested on the Federal Test Procedure for CO reveals that the FTP does not identify high-emitting vehicles on a gram per mile basis [CARB, 1993]. In other words, a visual 'best fit' line provides a slope of close to zero, which suggests that remote sensing results provide no useful information for predicting high gram per mile emitters, and vice versa. Essentially this means that high-emitters identified by remotely measuring tailpipe concentration are not necessarily high emitters on a gram per mile basis. This observation deserves further exploration.

When vehicles are identified via remote sensors as being high-emitters, we can be reasonably sure that the vehicle is in severe enrichment at the instant of measurement (the vehicle is not combusting it's fuel stoichiometrically and is running rich). Remote sensors identify high concentrations of CO, but cannot discern the volume of exhaust gases being expelled from the tailpipe. If a 'clean' car is identified by a remote sensor as a high emitter, it may still exhibit a very low

gram per mile emission rate, relative to dirtier cars with bigger engines. However, the remote sensor is still a useful tool for identifying potentially high emitting vehicles because combustion stoichiometry is based upon correct ratios (or concentrations) of fuel and air, which is measured (indirectly) by the remote sensor.

Identifying high-emitters via remote sensing is not likely to provide adequate information to estimate the impact of high emitters on the emissions inventory. However, remote sensing is useful for targeting poorly operating vehicles for clean up. Current evidence suggests that remote sensors can not adequately identify high gram per mile emitters, which is important for determining emission inventory impacts.

What is also important to note is that remote sensors only capture a 'snapshot' in time, and not the full emission profile of vehicles. This is extremely important when we consider the variability of vehicles across test cycles. Some vehicles register low gram per mile emissions on the FTP, yet register high gram per mile emissions on the high speed cycles. This has been shown with many vehicles and cycles contained in the existing speed correction factor database [Guensler, 1993]. Many vehicles exhibit erratic emissions behavior, where their behavior on one test cycle is not at all indicative of their behavior on an alternative test cycle. Some vehicles are high-emitters on high-speed cycles only, while others are high-emitters on low speed cycles only. The current EMFAC methodology predicts that vehicles exhibit systematic behavior across emission testing cycles.

Ambient Air Quality Monitoring Studies

Ambient air quality monitoring studies provide a relatively good source of data with which to compare model estimated emissions from motor vehicles. The advantages of these studies are that they provide virtually continuous (temporally) monitoring of air quality in a gridded fashion for a region; they provide relatively consistent CO/NOx and HC/NOx ratios, and they provide spatial information broad enough to provide air quality measurements for an entire air basin. The disadvantages are, however, that they measure all emissions in an air basin, not just motor vehicle emissions; the measurements are dependent upon spatial location, and atmospheric dispersion, and may not represent the most severe or extreme episodes; and the measurements can be heavily influenced by spatial and temporal variation in meteorological characteristics.

The South Coast Air Quality Study (SCAQS) included 11 intensive sampling days during the summer of 1987 spanning from June 19 to September 3, and included 6 intensive sampling days in the fall spanning from November 11 to December 11. A summary of the results are provided in Table 6.

Table 6- Mean of SCAQS Monitoring Results - All stations[a]

Study	CO / NOx	NMHC/ NOx	NMOG/ NOx
Summer Field Study	20.0 (0.7)	8.2 (0.2)	8.8 (0.2)
Fall Field Study	18.4 (0.9)	6.6 (0.5)	6.9 (05)
Mean Fall/Summer	0.92	0.80	0.78

[a] Adapted from Fujita, et al. 1992
  standard error of observed mean

When comparing emission derived results to ambient monitoring results, researchers found that ambient CO/NOx and NMOG/NOx ratios were 1.1 to 2.7 and 1.7 to 3.0 times higher, respectively, than the corresponding emissions ratios derived using EMFAC7E [Fujita, et al., 1992]. When considering dispersion effects and atmospheric chemical processes, they found that the most appropriate comparisons for fall were basin-wide overnight comparisons, and for summer were basin-wide 06 - 08 am comparisons. Considering these results, researchers found that ambient CO/NOx and NMOG/NOx ratios are about 1.5 and 2 to 2.5 higher, respectively, than corresponding emission inventory ratios [Fujita et al. 1992].

CONCLUSIONS

This paper has identified some of the shortcomings of the current emissions modeling procedures used to perform conformity analyses by transportation and air quality planning agencies in major metropolitan areas. The problems cited are just some of the major problems compromising the accuracy of existing modeling practice. There are others.

For example, we did not discuss the uncertainties associated with dispersion modeling. Nor did we the problems associated with data collection used to 'verify' transportation activity models.

Despite the serious problems we have identified, the current models are indeed very helpful and necessary tools with which to perform air quality and conformity analyses as directed by the Clean Air Act. Considering that the system we are trying to model is so complex and contains so many significant and important variables, it is no surprise that there are still errors. In fact, it is likely that we will never be able to predict some of the outcomes of the 'system' due to the presence of the human element.

The challenge, then, comes in trying to determine how precise and accurate we should strive to be in our predictions and modeling. This begs a question: What margin of error is acceptable in terms or accuracy, and similarly, what margin of error is acceptable in terms of precision?

Under ideal conditions, we want model outputs that are precise and accurate. In transportation emissions modeling, precision is not an issue. Every time the model is run for a certain scenario, the model predicts the same emission rate. Because the models are not Monte Carlo simulation approaches and do not employ probability distributions, the mean response values embedded in the models are consistent for each modeling run.

Model accuracy is another issue altogether. The mean emission responses described in the model algorithms are not necessarily accurate. As discussed previously, if these algorithms are based upon a poor representation of the vehicle fleet, or inappropriate statistical inferences, the results are not likely to be accurate. The net accuracy of the model is really a function of the contributing bias of individual model algorithms (e.g. speed correction, temperature correction, etc.) Realistically, however, the current emission and transportation activity models can be significantly improved.

Modeling biases lead to inaccurate models. For example, the trip distribution model has been criticized over-estimating near trips and under-estimating far trips [Dickey, 1983]. This consistent error might lead to the systematic over-estimation of cold starts, which in turn leads to overestimation of cold start emissions. These kind of errors in our models, systematic over or under predictions, are very serious and compromise our ability to ever predict the true population value. What makes model inaccuracies even more insidious is that they cannot be detected easily. To illustrate, consider the history of trying to reconcile regional emission model estimates with observed emissions (tunnel studies, remote sensing, ambient air quality monitoring studies). It is extremely difficult to determine the source of the model bias, as evidenced by the EMFAC 7G model improvement effort.

In the context of emissions and modeling requirements contained in the Clean Air Act, many of the inaccuracies presented in this paper result in inaccurate model predictions. The inability of regional activity models to characterize non-recurrent delay, for example, results in consistent under-estimation of congestion and emissions. Even more problematic is the fact that strategies designed to reduce non-recurrent congestion events (e.g. roving emergency vehicle

services and advanced traveler information systems) can not be assessed using the currently mandated modeling methods [Washington, 1995].

We must embark on a model improvement effort that identifies and corrects the systematic errors in the current modeling process. The problem is deciding whether to perform incremental changes to existing models, or whether to revamp the entire sequence of models. Fortunately, both approaches are being taken.

Perhaps one of the most significant improvements that can be done to improve the current emission models is to develop an emission model that employs traffic measures other than average speed to estimate emissions. As recent research has disclosed that vehicle modal activity [Leblanc et al, 1994; Washington, 1995] is extremely important in the calculus of emissions.

Improvements to emission models must be accompanied by improvements in regional activity models. Since regional activity models do not currently includes estimates for vehicular modal activity (acceleration, deceleration, cruise, and idle), the models are inadequate for input into a new generation of emission models. It is hoped that the emergence of both improved transportation activity and emissions models will occur simultaneously.

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