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Comparing Lifetime Emissions of Natural Gas and Conventional Fuel Vehicles: An Application of the Generalized ANCOVA Model

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ABSTRACT

New regulations and incentives are encouraging the use of clean, alternative fuel vehicles (AFVs) in urban areas. These vehicles are seen as one option for reducing air pollution from mobile sources. However, because of the limited number of AFVs on the road, little is known about actual lifetime emissions characteristics of in-use AFVs. This study describes the use of a generalized analysis of covariance model to evaluate and compare the emissions from natural gas vehicles with emissions from reformulated gasoline vehicles. The model describes fleet-wide emissions deterioration, while also accounting for individual vehicle variability within the fleet. This ability to measure individual vehicle variability can then be used to provide realistic bounds for the emissions deterioration in individual vehicles and the fleet as a whole. In order to illustrate the use of the model, the carbon monoxide, oxides of nitrogen (NO_x), non-methane hydrocarbon (NMHC), and carbon dioxide emissions characteristics of a fleet of dedicated natural gas Dodge Ram vans and a fleet of dedicated reformulated gasoline Dodge Ram vans operating in the U.S. government fleet are explored. The analysis demonstrates the utility of the statistical method and suggests a potential for natural gas Dodge Ram vans to be generally cleaner than their conventional fuel counterparts. However, in the case of NO_x and NHMCs, the analysis also suggests that these emissions benefits might be reduced over the vehicle lifetime due to higher emissions deterioration rates for natural gas vehicles. As this paper is aimed at illustrating the analysis of the covariance model, the results reported herein should be considered within the context of a more comprehensive study of these data before general conclusions are possible. Generalization of these findings to other vehicle models and alternative fuel technologies is not justified without further study.

IMPLICATIONS

As alternative fuel vehicles begin to penetrate urban transportation markets, analyses of lifetime vehicle emissions profiles over time are critical to understanding the impact of these new technologies and to guiding policy. In particular, methodologies for comparing emissions from alternative fuel vehicles to those from conventional vehicles must be developed and refined in order to enable meaningful comparisons. This paper illustrates a powerful statistical method for comparing emissions. The methods are illustrated with data on Dodge Ram vans. The results demonstrate the importance of properly accounting for variations in emissions from one vehicle to another and illustrate the necessity of considering lifetime emissions when comparing alternative fuel vehicles to their conventional fuel counterparts.

INTRODUCTION

According to the U.S. Environmental Protection Agency (EPA), highway vehicles (all vehicle types combined) contributed 63.6, 34.9, and 26.7% of total carbon monoxide (CO), oxides of nitrogen (NO_x), and volatile organic compound (VOC) emissions, respectively, in the United States in 1995.[1] Although many steps have been taken in recent years to control these mobile source pollutants, increases in vehicle miles traveled, changes in vehicle populations, consumer tampering, poor vehicle maintenance, and changing driving patterns have hampered these efforts.[2,3]

In the past, command-and-control technology-based standards have been the mechanism of choice for mobile source regulators. However, within the past decade a larger menu of policy options has developed, including inspection and maintenance programs,[4,5] random audits,[6] employee ride-sharing measures, size-based fees,[7] and marketable emissions permits.[8,9] Unfortunately, even these new approaches have had mixed success and suffer from their own political, technical, and implementation problems. In addition, the uncertainty involved in calculating the cost-effectiveness of each of these activities creates justification problems for the policy-maker.[10,11]

With the passage of the Clean Air Act Amendments of 1990 (CAAA) and the Energy Policy Act of 1992 (EPACT), the option to use cleaner burning fuels has emerged as a possible solution to mobile source air pollution. Oxygenated and reformulated fuels have shown promise in reducing criteria pollutants, and programs requiring the use of these fuels were explicitly outlined in the CAAA.[12,13] The use of "alternative fuels"—those defined as such by EPACT—represents yet another option. These fuels include natural gas, methanol, ethanol, propane, and electricity. EPACT identifies a variety of mandates that require fleet operators in metropolitan areas to begin purchasing vehicles that operate on these alternative fuels.[14]

Despite these activities, there are relatively few alternative fuel vehicles (AFVs) operating throughout the country (less than 0.2% of the national vehicle population), and even fewer are undergoing rigorous emissions testing. However, it is expected that these vehicles will begin to penetrate markets at significant levels in the near future. The number of AFVs that were in operation in the United States in 1998 was about 395,000,[15] but this number is expected to increase, with over 1 million annual AFV sales by 2005.[16,17] Given these trends, it is increasingly important that the long-term, in-use emissions of AFVs be evaluated and compared to conventional vehicles.

An increasing number of studies over the past several years have attempted to collect and analyze emissions from in-use AFVs (i.e., AFVs operating in normal, daily driving conditions), including Gabele[18] and Kelly et al.[19-21] Most suggest that AFVs are cleaner burning than conventional vehicles operating on reformulated gasoline (RFG); however, the results reported to date are not conclusive. Because of large emissions variability among individual vehicles (even those of identical makes and models operating on identical fuels) and emissions deterioration over the life of these vehicles, fairly large data sets are needed, along with the use of appropriate statistical procedures, to make reliable, definitive inferences.

Unfortunately, emissions testing programs are often under-funded and therefore do not monitor a sufficiently large sample of vehicles over a long-enough time frame to demonstrate statistically significant results. Also, many testing programs are not developed with an efficient experimental design, nor do they address the practical difficulties of acquiring emissions testing on identical vehicles at identical points in their lifetimes.

One significant data collection effort aimed at overcoming some of these deficiencies has been funded by the U.S. Department of Energy (DOE) and managed by the National Renewable Energy Lab (NREL). This program has collected emissions data from over 300 AFVs and gasoline control vehicles operating in the U.S. government fleet. These vehicles operate on a variety of fuels, including methanol blends, ethanol blends, compressed natural gas, and propane, and represent various driving conditions and operations. The National Alternative Fuels Data Center (AFDC), located in Golden, CO, collects and publishes data from these emissions tests.

In addition to inadequate experimental design and data collection strategies, many studies also fail to use appropriate statistical methods to characterize emissions deterioration. One common practice is to use conventional regression analysis to express emissions as a function of mileage (thereby indirectly accounting for aging effects). Such an approach does not adequately account for the inherent variation among individual vehicles within a fleet (i.e., all vehicles that are "identical" with respect to model and year). Hence, the resulting confidence bands for the average fleet-wide emissions profile, as well as the tolerance bands giving the expected range of emissions from individual vehicles, are often too narrow. This failure to account for vehicle-to-vehicle emissions also desensitizes statistical testing procedures, thereby making it more difficult to reliably detect differences between fleets and fuel types. The goal in this paper is to illustrate one approach that evaluates the functional relationship between emissions and mileage, but also attempts to properly incorporate and account for all of the major sources of variation in emissions. In doing so, a more complete understanding of deterioration among fleets and fuel types is possible.

The statistical approach described in this paper is a generalization of the classic analysis of covariance (ANCOVA). This approach is more reliable than conventional regression analyses because it accounts for both engine age (as indicated indirectly by odometer readings) and variations between vehicles of the same make and model. Furthermore, the generalized ANCOVA approach facilitates statistically reliable comparisons between vehicles operating on different fuels and leads to more accurate confidence bands for fleet-wide emissions and for individual vehicle emissions.

This ANCOVA analysis is demonstrated by analyzing CO, NO_x, NMHC, and CO_2 emissions from 58 in-use vehicles selected from the AFDC database. Twenty-seven of these vehicles (Dodge Ram vans) use dedicated, compressed natural gas (CNG). The remaining 31 vehicles are otherwise identical, but are dedicated to the exclusive use of California Phase II reformulated gasoline (RFG).

METHODOLOGY

The statistical model used in this study relies on the general methodology of ANCOVA discussed in Searle.[22] This model can be used to compare two or more "treatments" that have been applied to a population of individuals. In the present study, the population consists of individual vehicles assumed to be from a given fleet (make and model of cars). The "treatments" are the different fuel types that are to be compared. The response of interest is the emissions (grams/mile) of a given pollutant. The simplest ANCOVA model accounts for the fact that the response (i.e., emissions) depends on a "covariate" (i.e. mileage driven), which can change from one measurement to the next. In this sense, the ANCOVA model is a generalized application of the standard analysis of variance (ANOVA) in which one or more treatments are compared, but in which there is no covariate.

The model illustrated here generalizes the simplest ANCOVA model to also account for the random variation between vehicles within the fleet. By doing so, the analyst is afforded statistically sensitive and reliable tests for comparing deterioration rates among fuel types and for comparing emissions at any specified mileage. The approach is well established in the statistical literature (see Searle's text for details), but it has received little published attention in the field of emissions modeling (one exception is a study conducted at Battelle Memorial Institute[23]).

As mentioned earlier, the statistical analysis presented here was conducted on emissions values from the AFDC database for 27 compressed natural gas (CNG) Dodge Ram vans and 31 RFG counterparts, using data extracted on August 11, 1998.

Emissions tests on these vehicles were conducted at three commercial labs throughout the country which were selected through a competitive bidding process. A panel of experts (including EPA personnel) conducted site visits to assure that standardized testing methods were used across all three labs and that appropriate quality assurance procedures were in place. Each vehicle was tested using the EPA's Federal Test Procedure (FTP) protocol at accumulated mileage readings of approximately 4000 miles, 10,000 miles, and every 10,000 miles thereafter. For obvious logistical reasons, all the vehicles could not be tested at these exact mileage specifications. The general test procedures, emissions test driving profiles, and hydrocarbon speciation procedures, along with other facts about the testing program and vehicles, are reported elsewhere.[19-21]

Table 1 provides information about the vehicles, their fuels, and the number of vehicles per fuel type (sample sizes). Note that all the CNG vehicles are dedicated, original equipment manufactured (OEM) Dodge Ram vans (i.e., none of the vehicles is an "aftermarket conversion"). Although no data are available on exactly how each vehicle was used, it is assumed that all the vehicles experienced similar driving conditions. This assumption may not be valid, and thus should be considered when interpreting the results of this study.

Table 1. Information on vehicle types and fuels.

Vehicle Type	**N (by model year)**
Dedicated OEM	22 (1992)
CNG Dodge Ram B250 Van (CNG/Ram)	5 (1994)
5.2-L V-8 engine configuration	
Multi-point fuel injection	
4-speed automatic	
11.1–15.7 equivalent gallon fuel capacity	
6400 lb gross vehicle weight	
LEV-certified	
RFG Dodge Ram B250 Van (RFG/Ram)	11 (1992)
5.2-L V-8 engine configuration	20 (1994)
Multi-point fuel injection	
4-speed automatic	
35-gallon fuel capacity	
6400 lb gross vehicle weight	

As shown in Table 1, the AFVs come mostly from model year (MY) 1992, with fewer coming from MY 1994. The reverse is true for the RFG vehicles in the study. This discrepancy could jeopardize our ability to make comparisons of the CNG and RFG emissions if different emissions control systems were installed on vehicles from 1992, as compared to vehicles in 1994. This, however, is not the case; emissions control systems in MY 1992 and MY 1994 vehicles are identical for Dodge Ram vans. (Note, however, that the emissions control equipment for the CNG vehicles is designed for operation on CNG and is different from the equipment used in RFG vehicles). It is also important to recognize that these vehicles are 6–8 years old. The reader is encouraged to keep in mind the fast pace at which emissions control technologies may change (especially for new AFVs), and to take the potential for new technological advancement into account when interpreting the emissions results reported here. Beyond this issue, model year is given no further consideration in the modeling and analysis.

These NREL-tracked vehicles were FTP-tested several times at each of several different mileages. However, the AFDC database contained only a single weighted FTP (WT) test result for each vehicle at each mileage. The WT values represent a weighted average of the emissions results from three different test regimes: cold-start test, running test, and hot-soak test. These weighted values were used in our analysis. Vehicles were eliminated that were tested at only one mileage reading or if the difference in mileage between the first test and last test was less than 4000 miles. In addition, emissions tests at mileages less than 3000 were eliminated due to the possibility of a "green catalyst" effect.[24]

A comparative frequency distribution of the collective mileages with all tests on all 58 vehicles is shown in Figure

1. The average mileage for all tests on all CNG vehicles is 14,159 miles, with a median of 11,397 and a maximum of 45,159. The average mileage for all tests on all RFG vehicles is 20,217 miles, with a median of 17,206 and a maximum of 57,099. It is impossible to determine from the available data whether these differences are due to variations in trip duration, trip frequency, or both. It should be noted that the original experimental design specified that all vehicles be tested at the same mileage readings through the course of the study. This allows emissions profiles to be equitably monitored across all vehicles, thereby simplifying the interpretation of the analysis. Unfortunately, due to the logistical limitations and the large scope of this study, this ideal was not strictly achieved (as illustrated by the non-uniform distribution of mileages in Figure 1). While this departure from the intended design complicates the analysis somewhat, it does not invalidate the approach described here. Furthermore, the statistical model discussed below characterizes emissions deterioration only for the specific range of mileages covered in the data. At the outer limits of this range, the precision of the estimated profile is less than at the center of the range, where more data are available. This is reflected in wider confidence bands around predicted emissions at high mileages in Figures 2–5.

The model specifications are as follows: Let Y_{ijk} represent the natural log of the specific emissions constituent of the *k*th test on the *j*th vehicle that is operating on fuel type *i*. Let $m_{k(i,j)}$ stand for the *k*th mileage reading on car *j* operating on fuel type *i*. It is assumed that only one emissions result is obtained at each mileage reading on each vehicle (but the model can be generalized to handle replicate measurements). The model we employed has the form

$$Y_{ijk} = [\alpha + \beta^*\ln(m_{k(i,j)})] + [\phi_i + \delta_i^*\ln(m_{k(i,j)})] + [\nu_{j(i)} + \varpi_{j(i)}^*\ln(m_{\kappa(i,j)})] + \varepsilon_{ijk} \quad (1)$$

The first two terms $[\alpha + \beta^*\ln(m_{k(i,j)})]$ define the *average* dependence of the emissions on vehicle mileage, regardless of which fuel type is used or the peculiarities unique to individual vehicles within the fleet. The next two terms $[\phi_i + \delta_i^*\ln(m_{k(i,j)})]$ define how this average dependence is affected by fuel type *i*, and the last two terms $[\nu_{j(i)} + \varpi_{j(i)}^*\ln(m_{\kappa(i,j)})]$ define how the average dependence is affected by the unique characteristics of vehicle *j* that operates on fuel type *i*.

This model allows for the realistic situation in which there is an overall fleetwide deterioration curve that describes the average emissions for all vehicles in the fleet that are using fuel type *i*. The fleet-wide emissions curve when operating on fuel type *i* is defined by the expression $\alpha + \beta^*\ln(m_{k(i,j)}) + \phi_i + \delta_i^*\ln(m_{k(i,j)})$. However, the model also accounts for the fact that each vehicle in the fleet may have an emissions curve that differs slightly from the average fleet curve. This variation from the average curve can occur in either the intercept (through $\nu_{j(i)}$), the slope (through $\varpi_{j(i)}$), or through both the intercept and slope. The final term (ε_{ijk}) represents the random variation in emissions not accounted for in the model. This can include (but not be limited to) sources of variation from the test method used, differences between laboratories (if each car is tested at multiple labs), and so forth.

The assumptions behind this model are as follows:

(1) At a fixed mileage, emissions follow a log-normal distribution (i.e., the log of each specific emissions constituent follows a normal distribution). While this assumption is not critical to the use of the ANCOVA model (emissions could be modeled directly instead of using the natural log of emissions), it does provide a better fit for these data, and it is consistent with the procedures used in other studies;[23]

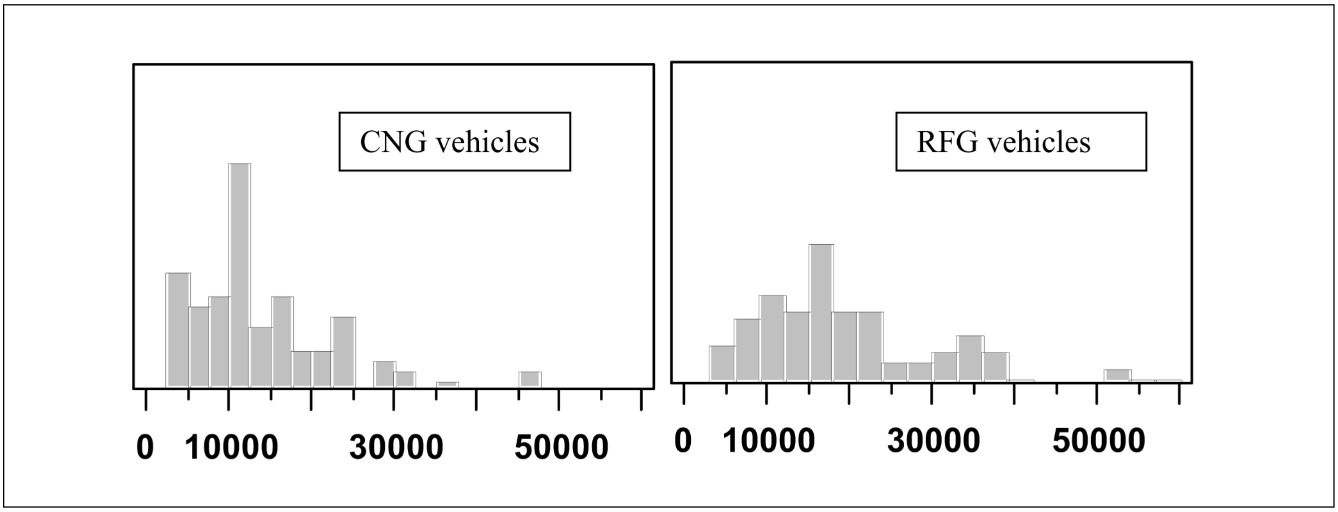

Figure 1. Odometer frequency distribution for CNG (left) and RFG (right) vehicles.

(2) The quantities α, β, ϕ, and δ_i in the model in eq 1 are fixed, but unknown quantities. If the study is aimed at characterizing the emissions profile of a fixed fleet of cars and for a fixed set of fuel types, then this assumption is reasonable. However, if the study's goals are to characterize emissions across a wide collection of fleets and fuel types, but data have been collected on only a random sample of fleets and a random sample of fuel types, this assumption must be relaxed. The present study (and probably most studies of practical interest) will satisfy the requirements implied by this assumption;

(3) $v_{j(i)}$, $\varpi_{j(i)}$, and ε_{ijk} are all random quantities. Each follows a normal distribution having a mean of zero. The standard deviations of these distributions are σ_v, σ_ϖ, and σ_ε, respectively. The standard deviations σ_v and σ_ϖ measure how much individual vehicle emissions profiles will vary around the fleet average emissions profile. That is, the larger σ_v and σ_ϖ are, the more an individual vehicle emissions profile can vary from the fleet average profile. While numeric estimates of σ_v and σ_ϖ are provided by the analysis, further detailed analysis of these quantities will be covered in another paper. It is also assumed that $v_{j(i)}$, $\varpi_{j(i)}$, and ε_{ijk} are each independent of each other, and that their respective values are independent from one vehicle to the next (for $v_{j(i)}$ and $\varpi_{j(i)}$) and from one emissions measurement to the next (for ε_{ijk}).

The reader should note that this model does not explicitly account for variation between the laboratories conducting the tests. The AFDC data analyzed in this paper were collected across three different laboratories, one of which was located at a high altitude. Lab-to-lab variation can in fact be a dominant source of variation in these types of measurements. However, the model will provide a reliable test for comparing emissions from the two fuel types provided that (1) each car was tested at only one lab and (2) within each lab, vehicles from both fuel types were tested. Both requirements were satisfied by these data. Furthermore, under these assumptions, the lab-to-lab variation will be accounted for in the model, but will be indistinguishable from vehicle-to-vehicle variability. Hence, if the analysis suggests a large variation between vehicles within the fleet, we cannot conclude that this source of variation is found only in differences between vehicles. It may partly be caused by variations between testing labs.

The analysis was conducted using PROC MIXED in the SAS statistics package (version 6.12) distributed by the SAS Institute, Inc.

RESULTS

This paper uses the ANCOVA model in eq 1 to determine whether statistically significant differences exist in the average emissions profile between vehicles operating on different fuels (CNG and RFG), while also accounting for the variations inherent from one vehicle to another. The emissions profiles generated by this model estimate the average emissions values that can be expected for a fleet of vehicles operating on each particular fuel type at any given mileage.

Average emissions values for each fuel type were determined by fitting the complete model discussed above. Parameter estimates and their variances were determined, allowing the generation of predicted values and confidence bands for the average fleet-wide emissions component of the model when operating on a particular fuel type; that is, values and confidence bands were determined for $ln(E_i)$, where E_i is the average emissions from vehicles when operating on fuel type i at a specific mileage m.

$$ln(E_i) = \alpha + \beta\, ln(m) + \phi_i + \delta_i\, ln(m)$$

These predictions can be converted to the original scale as follows:

$$E_i = e^{\alpha + \beta\, ln(m) + \phi_i + \delta_i\, ln(m)} \quad (2)$$

The emissions profiles in eq 2, along with their 95% confidence intervals, are plotted for each measured pollutant in Figures 2–5. Each figure shows the profiles and confidence bands for the CNG vehicles and their RFG counterparts.

Table 2 summarizes the results of standard ANCOVA F-tests used to compare the average *emissions profiles* between the two fuel types. The "F-test for slope" in Table 2 indicates whether the *rates* of emission deterioration are the same for both fuel types. The "F-test for offset" indicates if the two fuel types exhibit a *constant offset*, or difference in emissions at all mileage readings. This second F-test is meaningful only if the "slope" F-test is not statistically significant. Based on a 5% significance level, Table 2 indicates that the rates of deterioration are different for CO, NO_x, and NHMC and that there is a constant offset in emissions for CO_2.

Figures 2 and 5 visually display the difference in emissions profiles for both CO and CO_2. Note the negative slope for CO emissions from CNG vehicles and for CO_2 emissions from both CNG and RFG vehicles. These results compare well with an earlier study focusing on deterioration from a smaller set of vehicles.[24] In the cases of CO and CO_2, the confidence intervals for the emissions profiles do not overlap, and so CNG vehicles in both cases prove to be cleaner than their RFG counterparts.

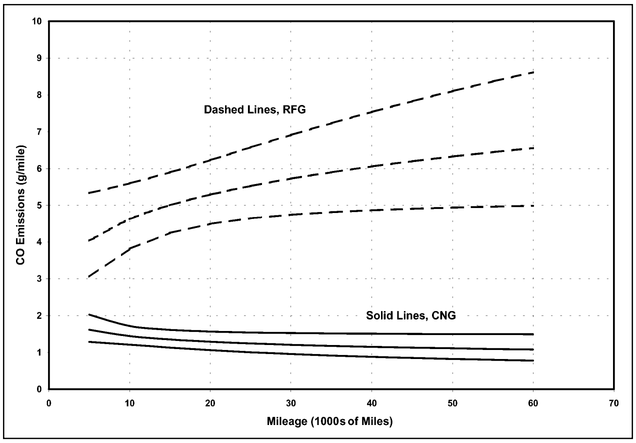

Figure 2. Fleet CO emissions profile with 95% confidence bands for Dodge Ram vans (gasoline versus natural gas models).

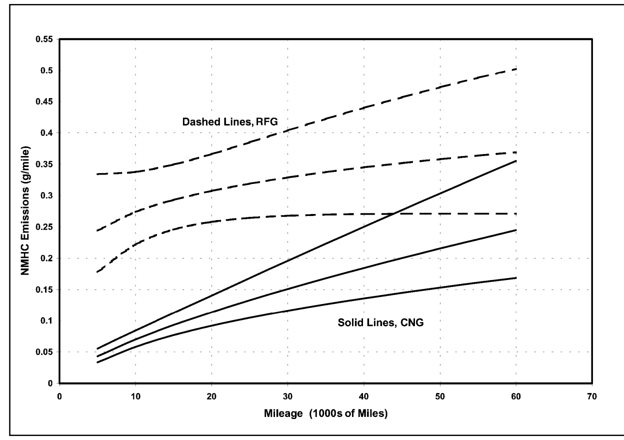

Figure 4. Fleet NMHC emissions profile with 95%confidence bands for Dodge Ram vans (gasoline versus natural gas models).

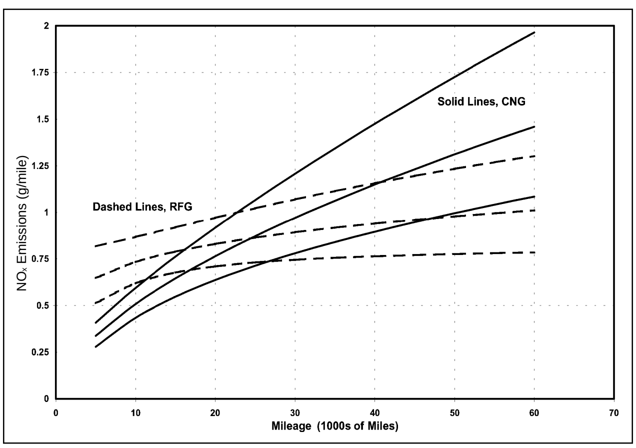

Figure 3. Fleet NO_x emissions profile with 95% confidence bands for Dodge Ram vans (gasoline versus natural gas models).

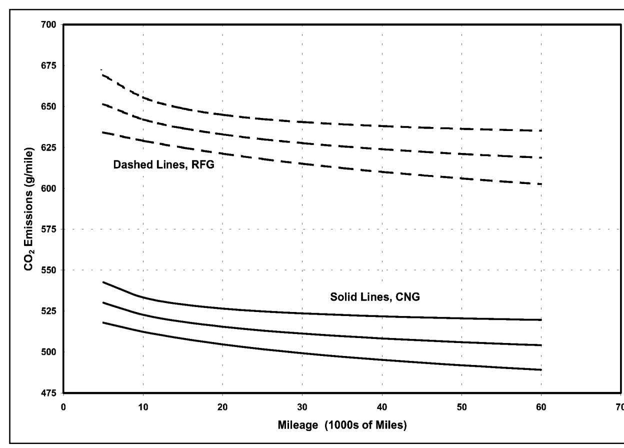

Figure 5. Fleet CO_2 emissions profile with 95% confidence bands for Dodge Ram vans (gasoline versus natural gas models).

A similar situation occurs for NMHC emissions (Figure 4) where CNG vehicles tend to be cleaner than RFG vehicles for most of the profile curve. However, at about 40,000 miles the confidence bands of the CNG and RFG vehicles overlap, and so emissions differences are less certain. This overlap in confidence bands is also seen throughout most of the NO_x emissions curve (Figure 3). These overlapping confidence bands make it unclear which fuel is cleaner with regard to NO_x over the mileages spanned in the dataset.

CONCLUSIONS

This paper describes a generalized ANCOVA model for characterizing emissions profiles among fleets of vehicles operating on different fuel types. The approach is illustrated on a data set composed of 27 CNG and 31 RFG Dodge Ram vans operating in the federal fleet. The analysis and discussion emphasizes that a proper analysis of emissions must consider (1) the emissions deterioration that occurs over the lifetime of a vehicle, (2) the emissions variability prevalent within individual vehicles, and (3) the emissions variability from one vehicle to another. Conventional regression analyses fail to properly account for (2) and (3). The ANCOVA model used in this study explicitly accounts for all of these factors and can be readily applied to more accurately characterize the emissions of any type of alternative or conventional fuel technology and vehicle fleets using those technologies. Moreover, by properly accounting for variation between vehicles, one can develop a more realistic understanding

Table 2. ANCOVA F-test results for comparing emissions profiles between CNG and RFG vehicles.

Pollutant	F-test for Slope (p-value)	F-test for Offset (p-value)
CO	Significant (0.0052)	Not applicable
NO_x	Significant (0.0002)	Not applicable
NMHC	Significant (0.0004)	Not applicable
CO_2	Not Significant (0.9568)	Significant (0.0406)

of the range of emissions values that are possible from any randomly chosen vehicle in the fleet. This range may in fact be dramatically different from what would be obtained from more classical regression models that fail to account for variations between individual vehicles. This type of understanding can be critical to policy-makers and researchers. Further work on this type of analysis will be pursued.

The specific analysis reported herein on Dodge Ram vans should be interpreted within the context of a more comprehensive analysis of the AFDC data. However, our results indicate that (with respect to CO and CO_2 emissions) the CNG Dodge Ram van has an emissions advantage over its conventional counterpart (within the range of mileages covered by these data). Analysis that leads to the type of information in Figures 2–5 is critical in understanding the role that AFVs in general can play in reducing mobile source air pollution. Again, one must consider the entire emissions profile when exploring air quality policies that provide mandates or incentives for the use of AFVs.

Ongoing research will use results similar to those presented here to predict lifetime emissions from various AFV technologies and to assess the costs and benefits of AFV-based air quality programs. However, it is probably premature to use the actual quantitative results (e.g., deterioration parameters) found in this study for modeling or policy-making purposes. These results are directly applicable only to the population of Dodge Ram vans and AFV technology represented by our data. Furthermore, a growing range of AFV technologies now exists and is being continually improved. Hence, emissions profiles similar to those found in this study should be developed for many other vehicle fleets and technologies before general conclusions can be made. As more AFVs accumulate miles and undergo emissions tests, more accurate and precise deterioration estimates can be determined and more general conclusions about the long-term merits of AFVs can be reached.

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