Title

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Authors

Brodrick, Christie-Joy
Sperling, Daniel
Weaver, Christopher

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Christie-Joy Brodrick, graduate student
Institute of Transportation Studies
University of California, Davis
Davis, CA 95616
phone: (916) 752-1934
fax: (916) 752-6572
cjbrodrick@ucdavis.edu

Daniel Sperling, Ph.D.
Director, Institute of Transportation Studies
University of California, Davis
Davis, CA 95616
phone: (916) 752-7434
fax: (916) 752-6572
dsperling@ucdavis.edu

Christopher S. Weaver, P.E.
Engine, Fuel, and Emissions Engineering
9812 Old Winery Place, Suite 22
Sacramento, CA 95827
phone: (916) 368-4770
fax: (916) 362-2579
csw-efee@holonet.net

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1.0 Introduction

Heavy-duty diesel vehicle use is expanding everywhere. In the U.S., California Air Resources Board (CARB) estimates that between 1990 and 2010, the number of trucks will increase by 70% and vehicle miles traveled will increase by 60% (CARB, 1998). In developing countries, the demand for freight movement and hence trucks will grow faster than gross domestic product and population (World Bank, 1996). The highest growth rates are predicted for Central and Eastern Europe, where trucking activity is expected to triple by 2015 (World Bank, 1996).

Heavy-duty diesel vehicles are a significant source of particulate (PM) and nitrogen oxide (NOx) emissions in the U.S. On-road heavy-duty diesel vehicles contribute 30% of PM and 65% of NOx created by on-road vehicles (CARB, 1997). Furthermore, diesel exhaust releases particles at a rate of about 20 times greater than gasoline-fueled vehicles.

In developing countries, it is estimated that motor vehicles contribute 60% to 90% of all urban air pollutants (WHO, 1996). A large obstacle to quantifying the contribution of heavy-duty diesel vehicles is the poor data quality and general lack of data on emissions in developing countries. However, it is well known that heavy-duty vehicles in developing countries, many of which are poorly maintained and over twenty years old, are major sources of urban pollution. The heavy-duty vehicle portion of emission in developing countries may not be as great as that in the U.S. due to the other significant sources of pollution in the developing world, such as two-stroke motorcycles and stationary industrial sources.

In both the U.S. and developing countries, interest in controlling diesel emissions has increased in response to mounting evidence that diesel exhaust has a highly adverse impact on health. Diesel exhaust includes over 40 substances that are listed by the U.S. Environmental Protection Agency as hazardous air pollutants and by the Air Resources Board as toxic air contaminants (CARB, 1998). Diesel particulate emissions specifically are under scrutiny due to the large quantity produced and their association with human respiratory problems. Exact biological mechanisms are not completely understood, but small particles (less that 2.5 microns in diameter) are believed to be pose the most severe health risks (Vedal, 1997). 92 percent of diesel particulates are less than 1 micron in diameter (CARB, 1998). These particles are in the size range that can be inhaled and eventually trapped into the bronchial and alveolar regions of the lung.

In the U.S., advances in engine design, fuel quality, and emissions controls, have led to a decrease in certified emissions level. Despite this, in-use PM emissions are estimated to be much greater than emission standards due to poor maintenance, general systems failures, and tampering. For the 1995 heavy-duty vehicle fleet, the average emissions increases over the useful life of a vehicle are estimated at 34% for VOC, 6.6% for NOx, and 43.7% for particulate (NRC, 1995). Because of the complexity and cost of emissions testing very few in-use emissions measurements have been made in developing countries. A rare World Bank study of bus engine emissions in Chile found that the in-use bus NOx and PM emissions increased by a factor of four due to poor maintenance and system failure (Escudero-Ortuzar, 1991). The large amounts of black smoke, which is an indicator of high emissions and vehicle malfunction, visible from vehicles in cities such as Jakarta, Bangkok, and Tehran, indicate that the trend is likely generalizable to many developing countries.

The most common approaches for reducing in-use vehicle emissions is conduct routine inspection programs, and require that improperly functioning vehicle be repaired. Heavy-duty vehicle inspection and maintenance programs are prevalent in the U.S. and gaining favor in developing countries. The potential impact of proper heavy-duty vehicle maintenance is illustrated by the Chile study where overhauls of buses resulted in a 75% reduction in particulate emissions (Weaver, 1996).

Options for inspection and maintenance programs include visual inspection, dynamometer testing, remote sensing, and smoke opacity testing. The criteria for selecting effective I/M programs includes cost, ease, safety, accuracy, and enforceability. The most accurate I/M procedure would be to measure emissions by running the vehicles on a dynamometer and analyzing the concentration of the specific pollutants, similar to what is done for light-duty vehicles in the California Smog Check II Program. However, even in developed countries, this is usually excluded as an option for heavy-duty vehicles due to the high costs of heavy-duty dynamometer testing and safety risks involved in testing poorly maintained heavy-duty vehicles. Recently remote sensing has been applied to heavy-duty vehicles, but it lacks the sensitivity to be used in enforcement programs. In the U.S., smoke opacity tests are most often employed as indicators of malfunctioning and hence high emitting vehicles because of the low-cost, ease, and safety.

There are five smoke opacity procedures, the snap-idle, idle, cruise, acceleration and lug-down, that are established tests for identifying malfunctioning engines in heavy-duty I/M programs. The most frequently used technique is the "snap-idle" (or "snap-acceleration"), that loads the engine using its own inertia, as the engine is rapidly accelerated from idle to full (governor-limited) speed. This technique and the smoke measuring equipment have been extensively defined in the Society of Automotive Engineers procedure SAE J1667 (SAE, 1994). This is the procedure used in California's heavy-duty on-road I/M program.

Unfortunately, the relationship between snap-idle smoke opacity tests and PM emissions are only fair-to-poor (Duleep, 1997). This is not surprising since PM emissions differ considerably depending on engine operation. The snap-idle or any of the other smoke tests alone are not representative of the myriad driving conditions where PM emissions vary. For example, a malfunctioning smoke puff limiter results in a thick black “puff” of smoke when a truck accelerates, but does not affect emissions under other conditions. This would produce very high smoke opacity measurements in the snap-idle test, but would have only a modest impact on PM emissions over the entire driving cycle. Conversely, a dirty air filter or worn fuel injector could double PM emissions over the entire driving cycle, but would have only a modest effect on smoke during acceleration. Thus, the snap-idle test could identify high emitters with malfunctioning smoke puff limiters, even if they were not especially high emitters of PM, but might not identify high PM emitters with dirty filters or poor injectors.

Since reduction of in-use PM is an increasingly high priority, it is desirable to develop a procedure that better identifies high PM emitters. The purpose of this research is to investigate alternatives to associating smoke to PM indirectly through vehicle malfunctions and to running expensive dynamometer tests. A desirable approach would be to run several smoke tests, which together were indicative of the PM emissions over a driving cycle. To date there has been no published effort to specify the relationship between PM emissions measured over a driving cycle and smoke from a combination of smoke tests. Since smoke opacity is directly related to PM (the Lambert-Beer Law) when both are measured simultaneously, it is hypothesized that measurements of smoke under a variety of driving conditions could be used to predict PM produced during a driving cycle by weighting several smoke test results by the portion of the driving that the smoke test condition represents.

To do this, smoke and PM levels in different modal operations (acceleration, deceleration, cruise, and idle) in the driving cycle would need to be characterized. Since current on-road smoke opacity tests are not necessarily indicative of driving cycle conditions, it is difficult to apply this weighting procedure to available smoke data to determine if smoke opacity measured under conditions characteristic of a driving cycle can be used to predict PM. Using existing data, it is possible, however, to apply regression models to investigate the potential relationship between a combination of conventional smoke tests and PM emissions over an entire driving cycle.

In this paper, the smoke-PM relationship is investigated in order to assess the potential for using multiple different smoke opacity test measurements as predictors of PM over an entire driving cycle. This was accomplished by developing regression models with PM over the entire driving cycle as the dependent variable and various smoke opacity test results as the independent variables. The objective was to identify in-use PM-smoke relationships emissions that could serve as an analytical basis for converting crude smoke enforcement programs into PM enforcement programs. These relationships could be applied in U.S. I/M programs as well as those in developing countries. The relationships considered were evaluated not only based on the accuracy of the procedure, but also the tradeoffs of cost, safety, and ease of administration.

2.0 Analysis of Smoke-PM Relationship

To determine the relationship between smoke opacity and PM, data from the New York City Department of Environmental Protection (NYCDEP) were used (NYCDEP, 1996). The NYCDEP, West Virginia University, and Colorado School of Mines have the only substantial data sets on HDDV PM and smoke opacity emissions. Data from West Virginia University were not used because the majority of data were for alternatively fueled heavy-duty vehicles, and fuel consumption data were not available. Data from Colorado School of Mines are proprietary and were not available. The NYCDEP data are for several types of smoke opacity and PM taken on vehicles between model years 1962 -1994.

2.1 NYCDEP Data

The usable data from NYCDEP included particulate and smoke opacity measurements from 147 diesel buses and 94 heavy-duty diesel trucks. For bus tests conducted after 1986, PM was measured for each vehicle on four different cycles: CBD15, N.Y. Bus Cycle-A, N.Y. Bus Cycle-B, and the N.Y. Bus Composite Cycle. For the majority of tests prior to 1986, bus data were available only for the N.Y. Bus Composite Cycle. Thus, in order to combine the pre-1986 and post-1986 databases, the data from the N.Y. Bus (NYBUS) cycle were used. The cycle average is 6.26 km/hr over a distance of 1.04 km in 600 sec. For trucks, two cycles were used by the NYCDEP: the N.Y. Truck Non-Freeway Cycle and N.Y.-L.A. Non-Freeway Cycle. As with the bus databases, there was only one cycle common to all records, the low-speed N.Y. Truck Non-Freeway Cycle, so data from this cycle were used for the analysis. The cycle has an average speed of 12.19 km/hr, and covers a distance of 3.41 Km in 1015 sec.

To control for the effects of test cycles variation on emissions, the NYCDEP PM measurements in g/mi were normalized to grams per gallon of fuel consumed, based on carbon dioxide emissions over the same test cycle. This assumed constant fuel use, which is not realistic. However, second by second emissions and fuel use data were not available. Five different smoke opacity measurements were made on each bus. These included cruise, idle, wide open throttle acceleration [WOT(A)], wide open throttle neutral [WOT(N)], and wide open throttle deceleration [WOT(D)]. The WOT(N) is comparable to snap-idle. Smoke opacity test for trucks included cruise, idle, and wide open throttle acceleration [WOT(A)]. A discussion of each of these tests as well as other common smoke opacity tests is included in the next section.

2.2 Smoke Opacity Test Description

The cruise smoke opacity test involves measuring smoke opacity for 5 to 10 seconds as a vehicle cruises at 30 mph. This test is most commonly conducted on a dynamometer, but it is possible to conduct the test on-road with a sufficiently large test area. Driver variability is a slight concern in this test, but the limiting factor is the space necessary for the test. Only nine buses and seven trucks in the NYCDEP database had cruise smoke over 1.5% opacity. All of these vehicles had high PM emissions in the range of 10 to 20 grams per mile (g/mi).

The idle test is simply a no load test conducted on a stationary vehicle in neutral. It is easily run on the side of the road, but shows a very poor relationship with PM emissions for modern vehicles. Only very high PM emitters generally display smoke during idle. In the NYCDEP database, the few vehicles with idle smoke opacity above 1% had PM emissions three to five times higher than vehicles with idle smoke opacity of 1% or less. For properly functioning, contemporary heavy-duty vehicles (model years 1988 to 1998), smoke opacity on cruise and idle tests is expected to be 0.5%.

On the WOT(N) or snap-idle smoke opacity test, the vehicle is put in neutral, and the accelerator is depressed rapidly to accelerate to governor speed. There is no additional load on the engine, and the test takes only a few seconds. It is favored for I/M programs because it is easily and safely conducted on the side of the road. As discussed previously, the smoke opacity emissions from a snap-idle test are not well correlated with PM.

The WOT(A) test procedure simulates real-world engine loading. The vehicle is accelerated to maximum governor speed while in low gear. This test is not considered practical for I/M testing because of the large space or heavy-duty dynamometers required. Even more important are safety limitations. Vehicles with poorly maintained brakes or throttles can accelerate out of control, so these vehicles are often rejected for dynamometer testing. Unfortunately, poorly functioning vehicles are often the same vehicles which are high PM emitters. The WOT(D) tests simulates real-world braking, and has the same safety problems as the WOT(A) test.

A sixth procedure, the brake lug down smoke opacity test, was not conducted by the NYCDEP. Since the lugdown test measures smoke opacity under a variety of vehicle operating conditions, it is the test that would have been most useful for this analysis. While there is much existing lugdown data, few vehicles have been tested for both lugdown smoke opacity and PM emissions. Lugdown tests, like acceleration tests, are a safety concern for poorly maintained vehicles.

2.3 Limitations

There are several limitations to using the NYCDEP data set. The NYCDEP data are nearly all for city-owned vehicles - primarily buses, but also smaller gross vehicle weight trucks. Thus, they are not representative any particular heavy-duty vehicle. There are a disproportionate number of low emitters, making up approximately 85% of the data. This is not necessarily unrepresentative, since it is generally believe that a few vehicles contribute the majority of emissions. It does present a problem, however, when trying to determine relationships between PM and smoke opacity. Often the decision whether to fit linear or nonlinear models to the data was based upon only a few points in the moderate to high emitter range. In many cases, polynomial regression models appeared appropriate, but the quadratic and cubic terms were consistently unnecessary based on t-tests. As a result, this analysis can only be considered exploratory in nature, and more high-emitter data would need to be gathered to properly fit the models.

A second limitation is that the lack of data on newer vehicles precluded development of relationships for several groups of buses and trucks. Perhaps the most severe limitation is that the data were collected over a fifteen year period with few records kept on modifications to the buses. Thus there are undefined variations in fuel composition, which has significant impact on the size and amount of particles. In analyzing the data, it is only possible to tell the model year of the vehicle, not the age of the engine. Thus, it is not possible to estimate the influence of engine replacement and vehicle age on the analysis

2.4 Regression Analysis of NYCDEP Data

The largest concerns with performing regressions on the NYCDEP smoke opacity and PM data were the possible endogenousness of the smoke and PM variables as well as the potential multicollinearity of the smoke variables. Endogeneity frequently occurs in econometric analysis where the independent and dependent variable are systematically related as in the case where price is the independent variable and quantity is the dependent variable. In this case, since PM measured over the entire driving cycle is measured in grams with no reference to particle size or chemical composition, and smoke opacity in a smoke opacity test is a function of particle size, number concentration, and optical properties (which in turn is a function of chemical composition), it does not appear that the variables are endogenous. Had an indicator variable such as HC data been available and had the data set been more complete, it would have been desirable to use two-stage least squares regression to avoid the possibility of endogenous variables. The indicator variable (HC) could then have been combined with the endogenous variable (smoke opacity) to come up with a proxy variable for smoke opacity. Since no indicator variable was available, the endogeneity of smoke and PM was doubtful, and the data set was incomplete, the decision was made to apply ordinary least squares regression.

In terms of multicollinearity, the first step in model development was construction of a correlation matrix to determine which variables were closely related. As expected, the various WOT tests were very highly correlated to one another. For example, for the pre-1985 model year groups, correlation coefficients between different WOT tests typically ranged from .75 to .99. Cruise and idle had the lowest correlations with each of the WOT variables (in the .50 and .30 range respectively). The correlations for peak WOT(N) were the least closely correlated with other WOT variables, however, correlations were still high (the correlation coefficient ranged from .61 to .71). To avoid potential multicollinearity problems, regressions were first limited to single independent variables with WOT(N), WOT(A), cruise and idle as the independent variables. An exploratory set of multivariate regressions was then generated by successively combining cruise smoke opacity as the first independent variable with each one of the WOT smoke opacity measurements as a second independent variable. This procedure was repeated for idle smoke opacity as the first independent variable. Unfortunately there were only a small number of idle and cruise smoke opacities that indicated more than a negligible amount of smoke. Thus, there were not enough data points to draw conclusions from the multivariate regressions.

The first analysis, determination of a relationship between wide-open neutral WOT(N) smoke opacity and PM, was conducted to confirm the commonly held theory that WOT(N) smoke opacity and PM are poorly related. It was chosen to use WOT(N) smoke opacity because it is very similar to snap-idle smoke opacity tests frequently conducted in I/M programs. If a relationship between PM and WOT(N) could be determined, PM emissions could be estimated from the vast amount of WOT(N) smoke data. Since heavy-duty I/M programs focus in trucks as well as buses, it would have been preferable to develop the relationships from PM and WOT(N) data on both types of vehicles, but NYCDEP did not perform the WOT(N) test on trucks.

A scatter plot of WOT(N) smoke opacity vs. PM was created for NYCDEP bus data for bus model years 1962-1994. The scatter plot reveals no discernable relationship between smoke and PM. It appears possible to have high WOT(N) smoke and low PM emissions as well as low WOT(N) smoke and high PM. Since different model year vehicles were subject to different emission standards, different emission control technology, and different engine design, it was hypothesized that the smoke-PM relationship could vary with these factors. Due to the lack of vehicle data on the NYCDEP buses, emission standards were the only factors available in addition to the smoke opacity of each bus.

Based on emission standards implementation dates, the data were divided into model year groups that were subject to the same standards. New scatter plots of WOT(N) smoke opacity and PM were created for pre-1985, 1985-1987, 1988-1990, 1991-1993, and 1994+ vehicle groups. For buses, there were only 15 observations in the 1991-1993 model year group and 4 observations in the 1994+ model year group, so no relationships were developed for these data. The 1988-1990 model year group had 18 vehicles, so only an exploratory relationship was developed.

Division of the data by model years reveals distinctly different pattern in the smoke-PM relationship. Most obvious is the large reduction in PM emissions after 1985. The scatter plot of PM vs. smoke opacity for the pre-1985 buses reveals that PM tends to increase with smoke opacity, but there are large variations in the PM levels that are recorded at each of the lower smoke opacity levels. For both linear and non-linear relationships, diagnostic plots revealed that none of the models attempted fit this data.

Despite the few data points for post-1985 model year vehicles, exploratory relationships were developed for WOT(N) smoke opacity and PM. The seven data points for 1990+ vehicles were all for vehicles with high PM and high smoke, whereas the data for 1985-1990 vehicles were all low to moderate emitters. As a result when the data were all combined into a post-1985 database, and nonlinear regression was attempted. The coefficient of determination as well as residual plots indicated that the models were poorly fit to the data. This is not surprising due to a large gap in the data due to there being a multitude of low emitters and only a few high emitters. Since it is likely that high emitters have a different relationship between smoke opacity measured over smoke opacity tests and PM measured over the full driving cycle, it seems probable that a polynomial regression model would fit the data best, but with so few data point on high emitters, it was not possible explore this.

As an alternative to grouping all the post-1985 data together, scatter plots of PM vs. WOT(N) smoke opacity for 1985-1987 and 1988-1990 model year buses are presented in Figure 1 and Figure 2 respectively. The coefficient of determination (R^2) for WOT(N) was .58, indicating that a fair amount of the variation in PM data was explained by WOT(N) smoke opacity (Table 1). A diagnostic plot of residuals vs. fitted values for 1985-1987 buses indicated a constancy of error variance and the residuals appeared normally distributed, so these models appeared appropriate. The residual plot for 1988-1990 buses, however, showed that the residuals may vary in a systematic fashion indicating that the model may not be appropriate for the data set.

Aside from the lack of fit of the regression models, two important trends appear in the scatter plots which confirm that WOT(N) smoke opacity may not be a good indicator of PM emissions over the full driving cycle. Many buses with a high smoke opacity reading in the snap-idle test also had high PM emissions. Some buses, however, exhibited high WOT(N) smoke while showing PM emissions only slightly higher than normal. In practice, this means that smoke opacity limits must be set high to avoid misidentifying low PM emitters. At the same time, many high PM emitters that do not have high smoke during snap-idle are missed.

The main focus of this paper was to determine if combination of a variety of smoke opacity test results would be a strong indicator of PM emissions. It was hypothesized that a combination of smoke measurements under full driving cycle conditions (low-load, steady-state conditions and transient accelerations) would yield PM-smoke relationships. Since there were too few data points with measurable cruise and idle smoke opacity, it was not possible to conduct meaningful multivariable regressions. Instead, scatter plots are presented to illustrate potential relationships.

The scatter plot of PM vs. cruise smoke opacity was created for all bus data. All of the data are plotted because there were too few vehicles with measurable cruise smoke in each model year group. The figure illustrates that all vehicles with detectable smoke opacity (smoke opacity greater than or equal to 2%) had higher PM emissions (PM greater than 10 g/mi). Unlike the WOT(N) or WOT(A) data, there were not instances where high cruise smoke opacity was associated with low PM emissions. This may indicate incorporating smoke opacity tests into on road tests would not identify all high PM emitters, and probably would not falsely indicate that a vehicle was a high emitter. Thus, the cruise test potentially could be incorporated to current on-road tests along with WOT(N) test, to identify high emitters and reduce the number of low emitters falsely identified by the WOT(N) test.

A similar analysis to the one above was conducted for WOT(A) smoke opacity. Although the acceleration smoke opacity test is generally not regarded as practical for on-road I/M application. As with the WOT(N) smoke opacity, a scatter plot of all truck data reveals no apparent relationship between WOT(A) smoke opacity and PM. Again, the data were divided according the emission standards that the vehicles were subject to. Since there were only 94 data points for trucks, the data were only divided into two categories: pre-1985 and post-1985. In general, WOT(A) smoke opacity were higher than WOT(N) measurements. This makes WOT(A) an attractive indicator, especially for newer vehicles where smoke opacity is very low. For low PM emitters, there were many instances where WOT(N) smoke was below 1%, but for these same vehicles, WOT(A) ranged from 1% to 15%. Thus, the WOT(A) appears to be a more sensitive indicator of PM.

The scatter plot of PM vs. WOT(A) data for pre-1985 buses indicates a possible linear relationship, while the scatter plot for post-1985 buses indicates a possible curvilinear relationship. For the post-1985 buses, t-tests indicated the quadratic and cubic terms in the curvilinear fit were unnecessary, so a linear model was fit. There were to few data point to confidently develop models, so exploratory models are presented in Table 2.

The results for truck PM-smoke relationships were very similar to the results for bus smoke-PM relationships. A scatter plot of PM vs. WOT(A) smoke opacity reveals that there is no discernable relationship between smoke and PM for all of the vehicles in the database.

The database was then divided into pre-1985 and post-1985 trucks. A scatter plot of PM vs. WOT(A) smoke opacity for pre-1985 trucks illustrates that there was a possible non-linear relationship between smoke and PM. A polynomial regression model was fit to the data, however, and again t-tests indicated the quadratic and cubic terms were not necessary, so a linear model was fit (Table 3).

As with the bus data, there were a few data points for high emitting trucks that did not follow the pattern of the rest of the data. This indicates that there is likely a different relationship between high and low emitters, and more data needs to be obtained for trucks with high smoke opacity to characterize these relationships. Another similarity to the bus smoke analysis is the high degree of variability in PM emissions at a single smoke opacity level. For a smoke opacity level of 18%, the PM level varied from 9 to 20 g/mi. While the level of variation for WOT(A) tests appears less than the variation for WOT(N) tests, the range of PM measurements that are seen at each level of smoke opacity is still undesirably large.

For post-1985 model year trucks, the majority of the data were for trucks between 1985-1987. The 1988-1990 and the 1991-1993 model year groups had only 7 and 6 observations, respectively. Scatter plots reveals no particular relationship nor could regression models be fit to the data.

Similar to the results for buses, a scatter plot of PM vs. cruise smoke opacity for trucks reveals that vehicles with non-negligible smoke during cruise had higher PM emissions. Like WOT(A) smoke opacity, there were a considerable number of PM emission levels associated with a single level of smoke opacity. However, unlike WOT(A) plots, there were no points where high cruise smoke opacity was associated with low levels of PM emissions. As with buses, this indicates that the cruise test may fail to identify some higher PM emitters, but a vehicle identified with high smoke at cruise, is likely a high emitter. Thus, the cruise test has the potential to be used to single out gross emitters that the snap test alone would miss.

If there had been more cruise data points, multivariate relationships would have been created to determine if combinations of WOT and cruise tests would be good predictors of PM. 1988-1990 model year buses and trucks were the only groups of data that had more than three cruise measurements above 1%. An exploratory analysis of PM relationships to WOT and cruise smoke opacity for these groups indicates that combinations of these tests are potentially good predictors of PM. Table 4 contains the regression models for the 1988-1990 buses and trucks.

3.0 Conclusions

Increasing evidence of the adverse health effects associated with diesel exhaust have prompted action to reduce heavy-duty diesel vehicle emissions. For inspection and maintenance programs in developing countries especially, it is desirable to use smoke tests as indicators of PM because smoke measurement is more suited to side-of-the-road application, and it is far less expensive and dangerous than actual PM measurement. Analysis of data from the New York City Department of Environmental Protection yielded only a fair-to-poor relationship between snap-idle smoke opacity, the most commonly use on-road smoke test, and PM. Wherever the smoke cut-off point was set, a significant number of vehicles were either falsely identified or missed. This indicates that snap-idle smoke opacity is not a strong approach for identifying high PM emitters.

The smoke-PM relationship may be improved by conducting a cruise smoke opacity test in addition to a WOT test. The few data that exist indicate that vehicles with high cruise smoke are consistently high PM emitters. As with the WOT(N) test alone, it is possible to have high PM emissions and low cruise smoke opacity. A WOT(A) smoke opacity tests may be superior to the WOT(N) test because of lower variation in PM at each level of smoke and better representation of lower smoke opacity levels. But its degree of superiority likely does not justify the added cost and equipment required to perform the test. A combination of WOT(N) and cruise smoke opacities appears to be the most promising identifier of high PM emissions. Exploratory analysis showed a combination of cruise and WOT(N) smoke were well correlated with PM. Currently, there is too little data to verify this relationship and quantify the impact of incorporating a cruise smoke test into I/M programs.

Figures

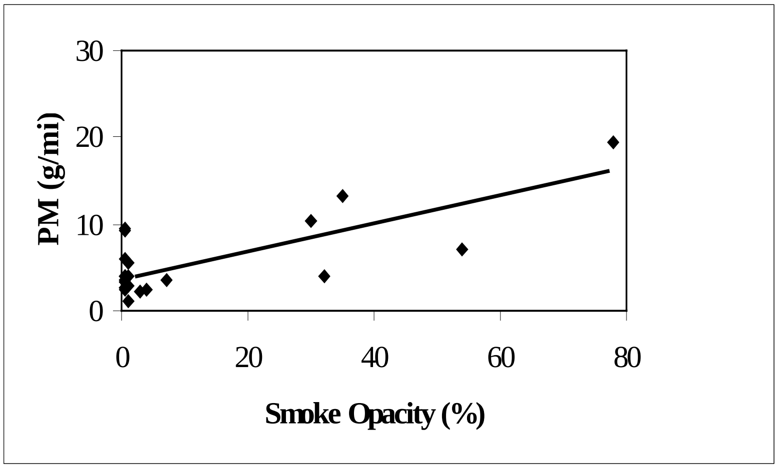

FIGURE 1 PM vs. WOT(N) Smoke Opacity for 1985-1987 Buses

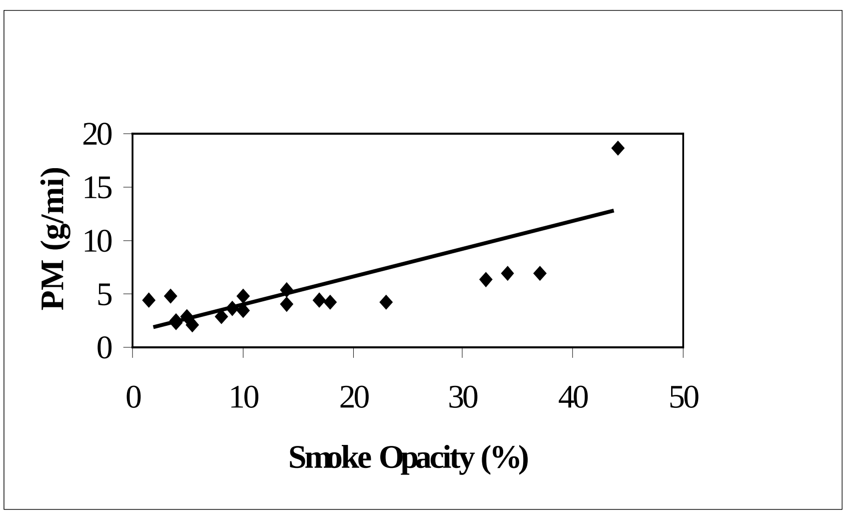

FIGURE 2 PM vs. WOT(N) Smoke Opacity for 1988-1990 Buses

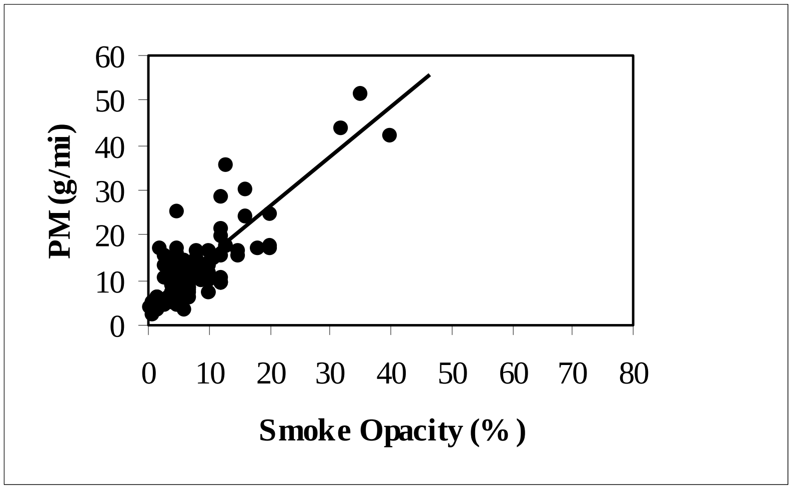

FIGURE 3 PM vs. WOT(A) Smoke Opacity for Pre-1985 Buses

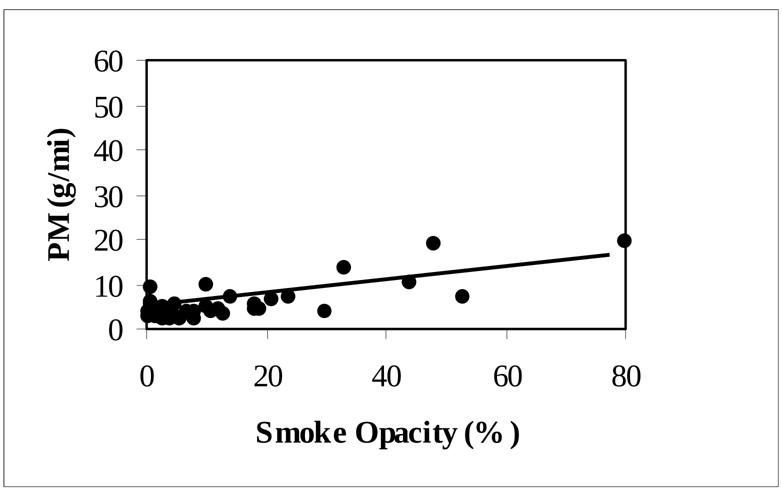

FIGURE 4 PM vs. WOT(A) Smoke Opacity for Post-1985 Buses

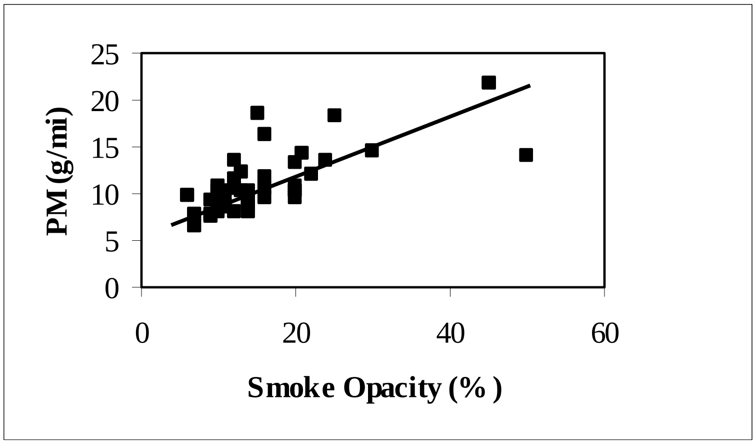

FIGURE 5 PM vs. WOT(A) Smoke Opacity for Pre-1985 Trucks

Tables

TABLE 1 Statistics for Linear Regressions on Bus PM Emissions

1985-1987 Buses: PM = 3.85 + 0.16WOTN

Variable	B	SE B	T	Sig T	C.I. Lower	Upper
WOTN	0.157	0.028	5.653	0.000	0.099	0.214
(Constant)	3.848	0.614	6.268	0.000	2.578	5.118

F-stat = 31.9, R^2 =.58, # observations = 24

1988-1990 Buses: PM = 1.67 + 0.216WOTN

Variable	B	SE B	T	Sig T	C.I. Lower	Upper
WOTN	0.216	0.044	4.946	0.000	0.124	0.309
(Constant)	1.668	0.867	1.924	0.071	-0.161	3.497

F-stat = 24.5, R^2 =.59, # observations = 18

TABLE 2 Statistics for Regressions on Bus PM Emissions

Pre-1985 Buses: PM = 3.66 + 1.06WOTA

Variable	B	SE B	T	Sig T	C.I. Lower	Upper
WOTA	1.060	0.073	14.564	0.000	0.915	1.204
(Constant)	3.657	0.743	4.9241	0.000	2.183	5.130

F-stat = 212.1, R^2 =.68, # observations = 101

Post-1985 Buses: PM = 3.02 + 0.184WOTA

Variable	B	SE B	T	Sig T	Lower	Upper
WOTA	0.184	0.021	8.548	0.000	0.140	0.227
(Constant)	3.024	0.438	6.190	0.000	2.142	3.907

F-stat = 73.1, R^2 =.63, # observations = 44

TABLE 3 Statistics for Regression on Pre-1985 Truck PM Emissions

PM =6.80 + 0.27WOTA

variable	B	SE B	T	Sig T	C.I. Lower	Upper
WOTA	0.270	0.036	7.451	0.000	0.197	0.343
(constant)	6.797	0.676	10.051	0.000	5.435	8.159

F-stat = 55.5, R^2 = 55.2, # observations = 46

TABLE 4 Statistics for Multivariable Regressions on 1988-1990 Buses and Trucks

1988-1990 Buses: PM=0.79+0.13WOTA+2.80C

Variable	B	SE B	T	Sig T	C.I. Lower	Upper
WOTA	0.128	0.041	3.117	0.006	-0.041	0.216
CRUISE	2.795	0.571	4.888	0.000	1.583	4.008
(Constant)	0.792	0.393	2.016	0.060	0.041	1.626

F-stat = 94.3, R^2 =.92, # observations = 18

1988-1990 Model Year Trucks: PM=0.50+3.39C+0.09WOTN

Variable	B	SE B	T	C.I. Sig T	Lower	Upper
WOTN	0.089	0.021	4.093	0.001	0.043	0.136
CRUISE	3.391	0.355	9.533	0.000	2.637	4.146
(Constant)	0.499	0.366	1.361	0.192	-0.278	1.277

F-stat = 122.3, R^2 = . 94, # observations = 13

References

California Air Resources Board. 1998. "Proposed Identification of Diesel Exhaust as a Toxic Air Contaminant", April 22, 1998.

California Air Resources Board . 1997. "The Heavy-Duty Vehicle Inspection Program (HDVIP) and The Periodic Smoke Inspection Program (PSIP)", October 1997.

Duleep, A.G.. 1997. "Smoke Opacity as an Indicator of Engine and Emissions Control Problems." Proceedings World Car Conference, Riverside, CA, January 11-14.

Escudero-Ortuzar, Juan. 1991. "Traffic and Air Pollution in Santiago, Chile". *PTRC Seminar on Civilizing Transport*; Vol. A; September 1991.

Jacobs, P. E., D.J. Chernich, and J.D. Kowaiski. 1991. "California's Heavy-Duty Vehicle Smoke and Tampering Inspection Program". SAE Paper 911669.

New York City Department of Environmental Protection. 1996. *Heavy-Duty Emissions Testing Records*. Frost Street Emissions Laboratory, NY.

National Research Council (1995). *Expanding Metropolitan Highways: Implications for Air Quality and Energy Use*. Transportation Research Board Special Publication 245; Washington, DC; 1995.

Society of Automotive Engineers. 1994. *Surface Vehicle Recommended Practice: Snap-Acceleration Smoke Test Procedure for Heavy-Duty Diesel Powered Vehicles*.

World Health Organization. 1996. Diesel Fuel and Exhaust Emissions. International Program on Chemical Safety, Geneva.

Vedal, Sverre. 1997. "Critical Review: Ambient Particles and Health: The Lines that Divide. Journal of the Air and Waste Management Association"; Vol. 47; May 1997.

Weaver, Chris. 1996. *Emissions Factors in Thailand and Chile*. Report to the World Bank.

World Bank. 1996. Sustainable Transport: Priorities for Policy Reform.

World Bank. 1998. Air Pollution from Motor Vehicles.