CHAPTER 1

INTRODUCTION

Emission modeling is a useful tool to estimate the pollution impact that motor vehicles have on the environment and human health. To better compute the fine-scale impacts of motor vehicles, emissions are modeled according to the vehicle operating mode, and are referred to as “modal” emission models. This thesis paper describes the development of an exploratory model of particle number emissions from a hybrid electric-diesel bus according to operating mode. There are several important aspects of the model. First, underlying emission data are measured in terms of particle number is instead of particulate matter mass. Second, the emission data are from on-board testing, in “real-world” driving conditions. Third, limited studies have been conducted on the benefits of hybrid-bus technology.

On-board emissions data bridges the disconnection between laboratory emission testing and “real-world” emissions. In the fall of 2001, the EPA explored the possibility of using on-board data in its new emissions model, MOVES, by conducting a “shoot-out” between several research organizations to test various approaches of using on-board data. It was found that “on-board data is a promising means for developing tailpipe emission estimates” (*1*). The emission data in this study is collected on a finely resolved scale, to facilitate modeling according to vehicle operating mode. Fine-scale, on-board emissions testing is becoming more widely used to support emissions modeling.

In this study, particulate matter emissions will be evaluated in terms of particle number instead of mass. The EPA currently regulates particulate matter (PM) emissions with two mass based metrics, PM_{10} and $PM_{2.5}$. These measurements sum the mass of particles with diameters smaller than 10 and 2.5 microns, respectively.

The $PM_{2.5}$ metric is designed to measure fine particles, however the number of ultrafine particles (diameter less than 100 nm) are not well represented. Ultrafine particles compose the majority of the number of particles, but only a minor proportion of the total mass, therefore a number based standard may be more appropriate *(2)*. Additionally, ultrafine particles may cause the highest health risks, due to their large relative surface area to mass, and ability to more easily penetrate the lungs *(3)*. Recently, European regulators have considered implementing a number-based PM standard for new vehicles *(2)*. Interestingly, lower PM mass based emissions from diesel engines do not always correlate with lower particle number based emissions (*4*). Thus, the significant vehicle/engine operating characteristics that affect PM mass emissions may differ when considering particle number emissions.

Reducing particulate matter emissions from urban transit buses can have a significant benefit to human health, due to their high particulate matter emission rates, and large exposure to people. The Clean Air Act Amendments includes an Urban Bus Retrofit/Rebuild program to reduce particulate matter from buses in large urban areas. Replacing conventional diesel buses with hybrid diesel-electric buses has been seen as a solution to lower PM emissions and comply with the program requirements *(5)*.

In August 2005, Holmén *et al. (5)* completed a study on particle emissions from both conventional diesel and hybrid electric-diesel buses with various diesel fuels and aftertreatments. One of the purposes of the study was to determine if hybrid electric-diesel buses produce less particle number emissions, or if apparent differences are attributed only to aftertreatment and fuel differences. The particle number concentrations for the two bus technologies were compared using the average concentration over multiple bus routes lasting several minutes. The study found no significant difference between particle number concentrations in hybrid electric-diesel and conventional diesel buses. However, examining the particle number emissions according to vehicle operating mode may elucidate the key differences between hybrid and conventional diesel bus particle emissions.

The objectives of the thesis paper are two-fold. First, it explores the feasibility of creating a sound regression model of particle number emissions from one route of a hybrid electric-diesel bus according to operating characteristics. Second, multiple operating characteristics are evaluating for their significance in predicting particle emissions. The operating characteristics include both velocity and acceleration along with several engine parameters. By including velocity and acceleration, this paper will address if they are important in predicting particle emissions, beyond their strong correlation with engine parameters.

CHAPTER 2

PARTICLE EMISSIONS DATA

The study by Holmén *et al.* evaluated two hybrid diesel-electric buses from the CTTransit (Connecticut Transit) bus fleet. The buses were model year 2003, equipped with Allison parallel hybrid transmissions and Cummins ISL 280 diesel engines *(6)*. The data evaluated in this study is obtained from one of the buses run on the Enfield route characterized by "high-speed steady-state freeway cruise on a commuter route" on August 3, 2004. The bus was run on ultra-low sulfur diesel fuel with a diesel oxidation catalyst *(5)*.

The particle number concentration was measured on-board using an Electrical Low Pressure Impactor (ELPI), after passing through a mini-dilution system. The ELPI measured the total number of particles for the range of 7 nm to 8μm. The dilution system is necessary to allow volatile compounds to form particles after leaving the tail pipe. To estimate the lag time for the exhaust particles to travel between the engine and the ELPI, the average time between engine start and first particle count was averaged from 48 engine starts. The average lag was 10.04 seconds with a standard deviation of 2.01 seconds *(5)*.

Scan tools were used to obtain vehicle and engine operating characteristics from the bus's diagnostic port and network. These parameters include percent engine load, engine speed, fuel rate, and vehicle velocity *(6)*. From velocity, acceleration was derived by taking the difference of speed, for each one second period. A calibrated pilot tube measured the exhaust flow rate *(5)*. The report by Holmén *et al.* is recommended if more experimental information is requested.

CHAPTER 3

ECONOMETRIC ANALYSIS

This paper describes the development of an econometric regression model used to explain particle number concentration from the operating characteristics of a hybrid-diesel electric bus. The particle number concentration is the dependent variable (Y), which will be explained by the operating characteristics of the bus (X). None of the characteristics are specific to hybrid vehicles, so the model parameters can be compared directly to a conventional diesel bus. The variables will be referred with the following notation throughout the analysis:

Y – Particle Number Concentration (#/cm^3) (in 10,000's)

X1 - Percent Engine Load, %

X2 – Fuel Rate, liters/hr

X3 – Engine Speed, rotation per minute (RPM) (in 100's)

X4 – Exhaust Flow Rate, liters/hr (in 1000's)

X5 – Velocity, mph

X6 – Acceleration, mph/sec (in 0.1's)

Variables Y, X3, X4 are scaled down, and X6 is scaled up so that each variable has roughly the same order of magnitude. This congruent scale assists in graphically evaluating the data, comparing coefficients, and minimizing numerical errors.

The X variables (bus operating parameters) contain data points for every second of the analysis. The Y variable (particle number concentration) is recorded roughly every other second. The route contains data collected just over 17 minutes, yielding 1,042 X observations and 549 Y observations. Multiple lags of the independent variable should be significant in the model due to the time lag between engine events and recorded particle number by the ELPI. The notation for the lags will be given in subscripts, for example $X1_{t-1}$ signifies a one period lag of percent engine load.

Disaggregated Data

A fine-scale regression model that predicts particle number concentration according to second-by-second operations is desirable. In this approach, the data is not aggregated; the Y data points are treated second-by-second with missing data points.

At the disaggregated level, the data are anticipated to contain two properties common to time-series data: autocorrelation and non-stationarity. Autocorrelation exists when the deviations of the regression are not independent from other deviations throughout time *(7)*. Non-stationarity exists when the dependent and independent variables exhibit trends through time *(8)*. When the regression variables are autocorrelated, parameters for regression models can still be estimated. However, unless the data can be transformed to be stationary, the regression parameters will be meaningless *(7)*.

By graphing the variables through time, the variables are evaluated for nonstationarity. Figure 1 shows an example of two operating parameters plotted through time: fuel rate and acceleration. The distribution of the variables appears to change with time, clearly showing that the distribution is not independent with respect to time. This property is referred to as nonstationarity, and all of the X-variables, and the particle number concentration exhibit this property. Nonstationary variables can produce a consistent regression if the variables are cointegrated. Cointegration occurs when the variables used in the regression drift at the same rate, and can be determined when the residuals of Y regressed on the X variables are stationary *(7)*. Particle number concentration was subsequently regressed on the variables X1 through X6, however the residuals are nonstationary.

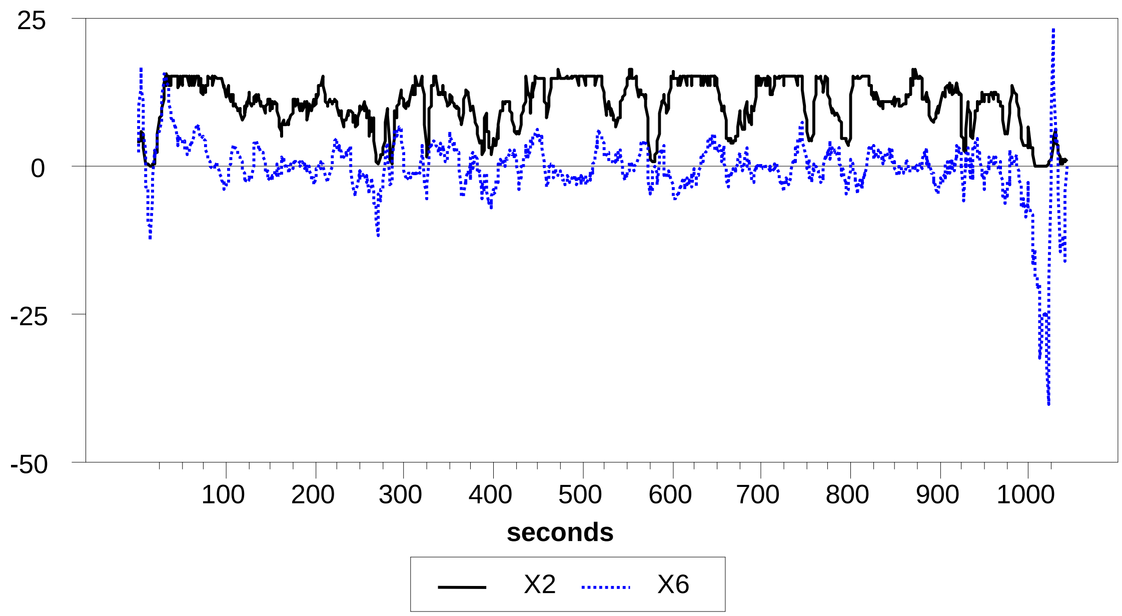


Figure 1 Second-by-second fuel rate (X2) and acceleration (X6) variables

There are several options to deal with nonstationarity in econometric analysis. One method is to eliminate trends by transforming the variables. A common transformation is to take the first difference of the variables ($x_t - x_{t-1}$), yielding Δx_t. The transformed variable Δx_t is then used as an independent explanatory variable *(8)*. Another approach to deal with nonstationarity in time series data is to aggregate the data. This method is possible when the data do not exhibit general increasing or decreasing trends.

Both methods have advantages and disadvantages. By transforming the variables, the fine-scale of the regression model is kept, however the explanatory variables are changed from the original data. For example, the regression analysis will not quantify the relationship between particle number concentration and fuel rate, but will explain the relationship with respect to changes in fuel rate. Another concern is that inconsistent lags occur in the data due to missing Y observations. The differencing transformation will result in Δx_t of varying time intervals between variables. This would introduce more problems than it would eliminate, thus the data were aggregated to larger intervals.

Aggregated Data

The data was aggregated to ten second discrete bins, reducing the number of Y and X variables to 104 data points for each variable. A ten second interval was selected because it is consistent with the anticipated lag between engine events and particle number count, and should be large enough to correct for nonstationarity yet small enough to capture vehicle operating modes. Aggregating the data should also reduce the autocorrelation of emission data, as confirmed by Frey et al. in gaseous emissions of light-duty vehicles *(1)*.

The stationarity of the aggregated data is evaluated to determine if the ten second aggregation interval is sufficient. In Figure 2 fuel rate and acceleration are graphed, showing that much of the non-stationary trends exhibited in the disaggregated data have been eliminated. The same results were obtained for the other variables, including particle number concentration. The analysis will continue treating the aggregated data as stationary.

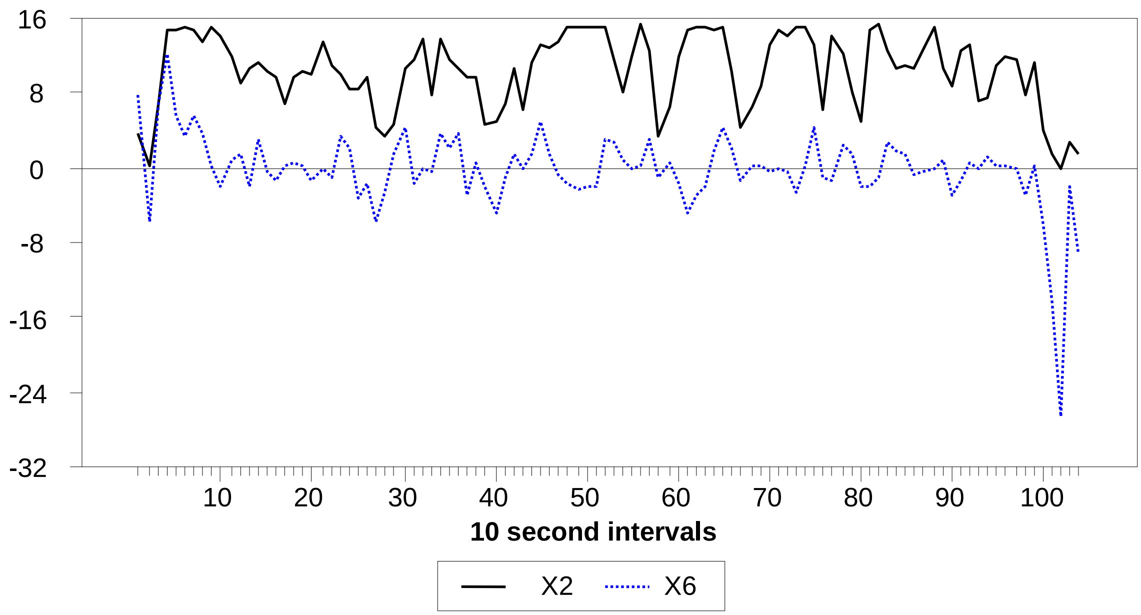


Figure 2 Ten second aggregated fuel rate (X2) and acceleration (X6)

Multicollinearity

Multicollinearity occurs when the independent variables are highly correlated to each other, which the bus operating characteristics are anticipated to possess. Multicollinearity does not affect the assumptions of least square regression, but it can lead to high standard errors of the coefficient estimators. A regression model with collinear variables may have a high goodness of fit, with none of the variables statistically significant. This can make it difficult to determine the most important parameters to include in the emissions model. Multicollinearity also causes coefficient estimators to change widely, including magnitude and even sign changes, with small changes in data *(7)*.

To evaluate the multicollinearity in the ten second aggregated data, each X-variable is regressed on all of the other independent variables. The R^2 of the regression determines the correlation between the variable and the other variables.

The variance inflation factor (VIF) is calculated from each R^2 to assist in judging the relative multicollinearity associated with each variable. VIF is calculated as:

$$VIF = \frac{1}{(1 - R^2)}$$

R^2 values close to one and large values of the VIF infer variables with high multicollinearity *(7)*. The R^2 and VIF values, reported in Table 1, indicate that percent engine load (X1) and fuel rate (X2) exhibit high multicollinearity with other X-variables.

Table 1 R^2 and VIF Values from Cross-regressing of X-variables

	Multicollinearity		Collinearity, R^2				
	R^2	VIF	X1	X2	X3	X4	X5
X1	0.989	89					
X2	0.992	122	0.96				
X3	0.904	10	0.39	0.56			
X4	0.375	1.6	0.14	0.16	0.19		
X5	0.496	2.0	0.12	0.17	0.43	0.12	
X6	0.455	1.8	0.25	0.19	0.03	0.24	0.03

To examine the causes of the multicollinearity further, each X-variable was regressed on other X-variables individually. The R^2 values of these regressions given in Table 1 under Collinearity show a maximum correlation of 0.96 between percent engine load (X1) and fuel rate (X2). This is not unexpected because percent engine load is estimated by the vehicle's electronic control unit based on the fuel rate *(9)*. Removing either X1 or X2 should not significantly reduce the predictive power of the model, and will reduce the multicollinearity of the model. Intuitively, particle number emissions should be proportional to the amount of fuel consumed, thus fuel rate will be included in the model and percent engine load will be discarded.

Model Selection Criteria

Ordinary least square (OLS) regression is used to identify significant lags in the model, with heteroscedasticity and autocorrelation evaluated later. Three goodness of fit criteria (Adjusted R^2, Akaike, and Schwartz) are implemented. Each of these criteria penalizes for excessive lags and variables. The Akaike and Schwartz criteria tend to implement a higher penalty for loss of degrees of freedom than the adjusted R^2 *(7)*. Because the measured lag at engine start between an engine event and particle count is approximately ten seconds, at least one period lag should be included in the model for the ten second aggregated data. As a first run, the contemporaneous and first and second lagged variables were included in the model. Multiple OLS regressions were conducted by adding and subtracting lags until the model selection criteria was optimized. The adjusted R^2 value with the highest value suggests the best fit, whereas the smallest value for the Akaike and Schwartz criteria suggests the best fit *(7)*. The lag scenarios with the best fit are listed in Table 2, with the optimal value for each criterion shown in bold font.

Table 2 Goodness-of-fit criteria for Y regressed on variables X2 through X6

Lags	Adjusted R^2	Akaike	Schwartz
0 to 4	**0.742**	3.16	4.36
1 to 3	0.671	3.57	**4.30**
0 to 8	0.672	**2.83**	5.02

The three different goodness-of-fit criteria suggest three different models. The analysis will proceed with the model suggested by the Schwartz criteria, because it included the fewest lags. Ideally, a modal emission model should not be correlated with engine events far into the past. The optimal Schwartz model does not include contemporaneous engine or vehicle events. This exclusion agrees with the estimated ten second lag time between engine events and measurements of the particle number concentration by the ELPI.

Heteroscedasticity Tests

The model selected from the OLS regression was examined for heteroscedasticity problems. OLS regression in the presence of heteroscedasticity will still produce unbiased estimates of model coefficients, however they will no longer be efficient. In econometrics, an inefficient estimate means the accuracy of the standard errors is no longer assured to be valid. This will reduce confidence that the model coefficients are close to the true values. Also, the statistical tests used to determine the significance of model parameters are no longer applicable *(7)*. Heteroscedasticity occurs when the disturbances from the regression do not have constant variance. The residuals squared from the regression (e^2) are plotted against model predictions of particle number concentration (Y estimate) in Figure 3. Visually, there does not appear to be a significant change in residual variances with respect to the estimate of Y.

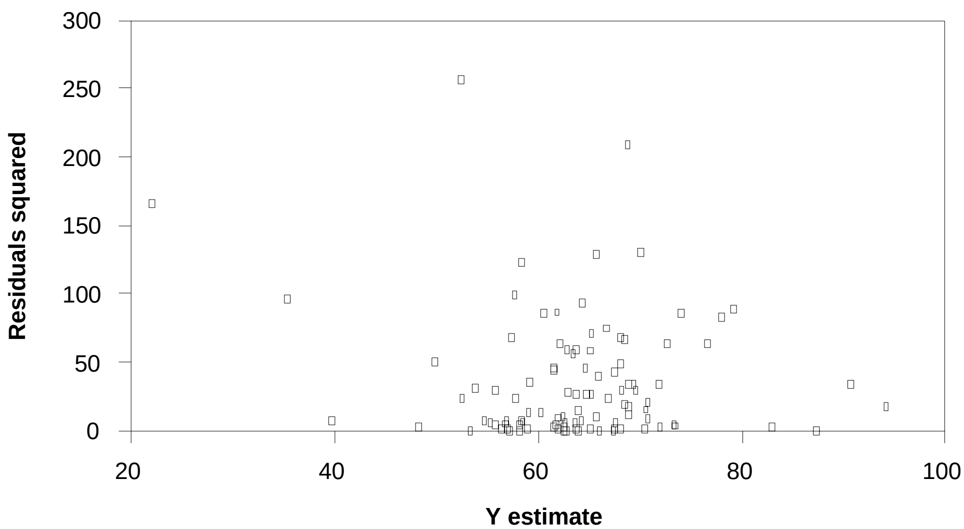


Figure 3 Residuals squared plotted against the Y estimate

To quantitatively evaluate if the disturbances are heteroscedastic two statistical tests were performed. First, the data was tested using the Breusch-Pagan Lagrange multiplier test, which yields a p-value of 0.026 signifying that heteroscedasticity is significant. Next, the Goldfeld-Quandt test produces a p-value of 0.304, suggesting that even if heteroscedasticity exists, it is not significant *(7)*. To be conservative, the study will continue with the assumption that the heteroscedasticity is significant.

Autocorrelation Tests

As stated previously, aggregation is a technique used to minimize the effects of autocorrelation often found in time-series data. To examine if the aggregated data still exhibits autocorrelation, the residuals are plotted against the lagged residuals in Figure 4. Visually, the residuals and lagged residuals appear to be positively correlated. Quantitatively, the Breusch-Godfrey test yields a test-statistic at a p-value of 0.0009, indicating significant autocorrelation. As with heteroscedasticity, autocorrelation violates one of the key principles of ordinary least squares, and causes the model coefficients to be inefficient, though still unbiased *(7)*.

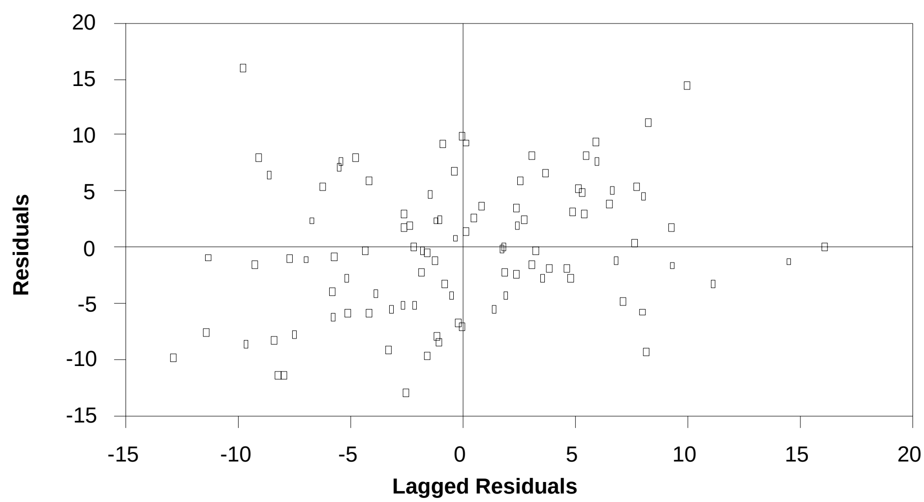


Figure 4 Lagged residuals plotted against residuals from OLS of Y on X2-X6

Newey-West Estimation

There are several methods to deal with data that has heteroscedasticity and autocorrelation properties. One robust method is to use the Newey-West autocorrelation consistent covariance estimator. This process uses OLS, but corrects the standard errors due to autocorrelation and heteroscedasticity. Further, Newey-West does not require any assumptions on the structure of the covariance matrix *(7)*. This method is run on the recommended Schwartz model, and the results are presented and compared to OLS estimates in Table 3.

Table 3 Model using OLS with Newey-West Estimator

		OLS		OLS with Newey-West	
Variables	Coefficients	Standard Error	Significance	Standard Error	Significance
Constant	25.59	10.18	0.01	10.00	0.01
$X2_{t-1}$	-2.09	0.61	0.001	0.50	0.00003
$X2_{t-2}$	-0.23	0.39	0.55	0.40	0.56
$X2_{t-3}$	-0.47	0.33	0.16	0.31	0.13
$X3_{t-1}$	3.03	0.76	0.0001	0.59	0.0000003
$X3_{t-2}$	1.60	0.75	0.04	0.73	0.03
$X3_{t-3}$	-0.04	0.70	0.95	0.46	0.93
$X4_{t-1}$	-0.12	0.40	0.76	0.39	0.75
$X4_{t-2}$	-0.09	0.60	0.89	0.53	0.87
$X4_{t-3}$	-0.85	1.03	0.41	0.84	0.31
$X5_{t-1}$	-0.68	1.71	0.69	1.46	0.64
$X5_{t-2}$	-0.84	1.45	0.56	1.41	0.55
$X5_{t-3}$	1.18	1.92	0.54	1.37	0.39
$X6_{t-1}$	1.95	0.71	0.01	0.78	0.01
$X6_{t-2}$	1.46	2.02	0.47	1.66	0.38
$X6_{t-3}$	1.48	1.01	0.15	0.65	0.02

As shown in Table 3, the Newey-West estimator does not change the coefficients or goodness-of-fit of the model. However, the standard errors are corrected to new values. All the standard errors save $X2_{t-2}$ and $X6_{t-1}$ decrease, which making the model variables more significant. The model is then revised by removing insignificant variables using joint F-tests. Joint F-tests are used because although individual variable and lag combinations may be insignificant (e.g. $X5_{t-1}$, $X5_{t-2}$ and $X5_{t-3}$), collectively the variables are significant. Each variable at the three lags is jointly tested, as well as each specific lag across all variables. Exhaust flow rate (X4), was found to be insignificant and is removed. All the other variables and lags are jointly tested to be significant and retained in the final model as reported in Table 5.

First-Order Autoregressive Process, AR(1)

To assess the robustness of the Newey-West OLS model, the data will be modeled using a First-Order Autoregressive Process or AR(1). AR(1) is a popular approach that uses feasible generalized least squares (FGLS) to model data that violates the OLS assumptions of no autocorrelation *(7)*. The AR(1) process uses the autocorrelation of past observations to predict future observations, by assuming the that the disturbances behave accordingly:

$$\varepsilon_t = \rho\varepsilon_{t-1} + u_t$$

where: ε is the disturbance from the OLS regressions

ρ is the correlation parameter

u_t is a nonautocorrelated white noise process

In order to validate the AR(1) assumption, the following regression is performed

$$\varepsilon_t = \beta_0 + \beta_1\varepsilon_{t-1} + \beta_2\varepsilon_{t-2} + u_t$$

If the AR(1) assumption is correct, β_1 should be statistically significant and β_2 should not. The residuals from the Schwartz OLS model are regressed on a constant and two lags of the residual. A t-test is used to test the significance of β_1 and β_2. The β_1 term is found to be significant while β_2 is not at the 95% significance level. Therefore, it appears that an AR(1) process is a reasonable assumption.

By incorporating the autocorrelation structure, the AR(1) FGLS regression changes the coefficients and standard errors from the OLS model parameters as shown in Table 4.

Table 4 FGLS AR(1) Model

Variables	Coefficients	Standard Error	Significance
Constant	22.42	9.74	0.02
$X2_{t-1}$	-1.33	0.34	1E-04
$X2_{t-2}$	-0.86	0.33	0.01
$X3_{t-1}$	3.15	0.69	1E-05
$X3_{t-2}$	1.80	0.68	0.01
$X5_{t-1}$	-1.32	1.14	0.25
$X5_{t-2}$	0.95	1.17	0.42
$X6_{t-1}$	2.18	0.58	0.003
$X6_{t-2}$	1.74	0.76	0.02
ρ	0.018	0.09	0.84

Joint F-tests are performed to remove insignificant variables and lags. Again the exhaust flow rate (X4) is found insignificant and is removed. Further, the third period lags across all variables are also insignificant, and removed from the model. The *p*-value of the correlation coefficient (ρ), increased considerably after the third period lags are removed. Although the correlation coefficient is no longer significant, it is not removed because the AR(1) process is the key underlying assumption of the model. The final AR(1) model coefficients appear in Table 4.

CHAPTER 4

MODEL COMPARISONS

Table 5 summarizes and compares the two models obtained from Newey-West and AR(1) FGLS regression. The coefficient estimates are fairly close between the two models. In both models exhaust flow rate (X4) is found insignificant and removed. Exhaust flow rate does not seem to have an effect on particle number concentration, although it will be important parameter if the particle number emission rate were considered.

Both models included the operating characteristics lagged 10 and 20 as important in predicting particle emissions. The OLS Newey-West model further retained the operating characteristics lagged 30 seconds as significant. There is an anticipated 10-second lag between when the exhaust leaves the engine and when it is measured by the ELPI. The model results imply the exhaust lag may be longer during bus operation, and/or particle number emissions are dependent on operating characteristics up to 10 or 20 seconds before engine events that form the particles occur.

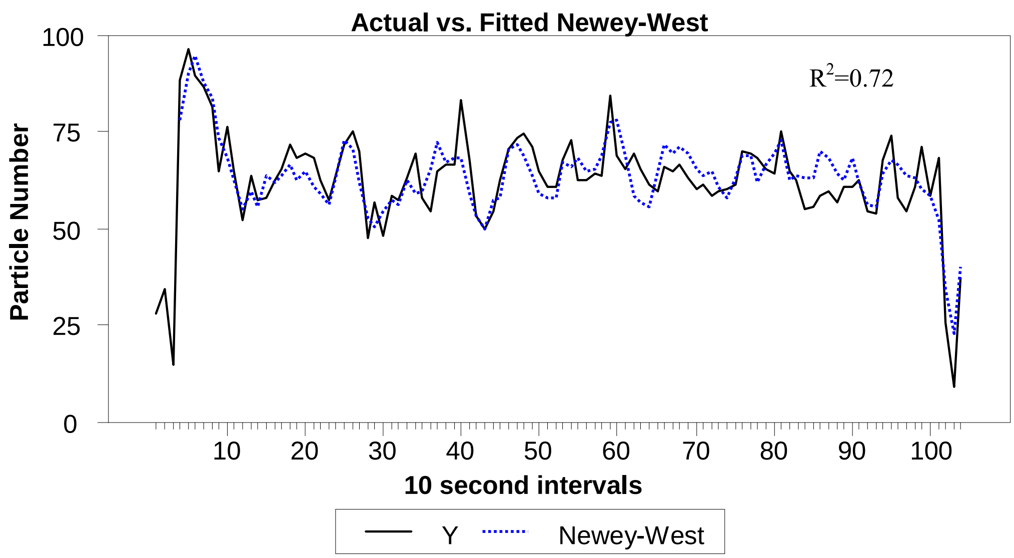
By incorporating the autocorrelation of particle emissions, the FGLS AR(1) model found the third period lags to be not significant (NS). Because the number of significant lags was reduced, the AR(1) FGLS could be viewed as a more efficient method to model emissions with significant autocorrelation. However, there is debate in the econometrics literature whether correcting a model for autocorrelation errors is appropriate. Some suggest that a better approach is to revise the structure of the model, for example including more lags or variables that account for the autocorrelation *(7,10)*. From a more practical point of view, an AR(1) model requires past emission values to predict future values. This is not desired because one of the purposes of the model is to predict particle emissions from only operating characteristics.

Table 5 Newey-West and AR(1) Model Comparisons

	OLS with Newey-West		FGLS with AR(1)	
Variables	Coefficients	Joint Significance	Coefficients	Joint Significance
Constant	23.65	0.01	22.42	0.02
$X2_{t-1}$	-1.62	7E-08	-1.33	1E-06
$X2_{t-2}$	-0.34		-0.86	
$X2_{t-3}$	-0.45		0	NS
$X3_{t-1}$	3.29	< 1E-8	3.15	1E-08
$X3_{t-2}$	1.67		1.80	
$X3_{t-3}$	-0.09		0	NS
$X5_{t-1}$	-1.15	0.02	-1.32	3E-03
$X5_{t-2}$	-0.72		0.95	
$X5_{t-3}$	1.54		0	NS
$X6_{t-1}$	2.10	2E-07	2.18	1E-03
$X6_{t-2}$	2.01		1.74	
$X6_{t-3}$	1.66		0	NS

For the purposes of this study, the AR(1) model appears to be an appropriate model to compare with the OLS Newey-West model. The model coefficients are similar in terms of magnitude and sign. All of the first and second lag variables have the same sign except the second period lag of velocity ($X5_{t-2}$), which is negative in the OLS Newey-Westmodel. The models show that in the presence of the four variables, fuel rate has a negative relationship with particle emissions, engine speed and acceleration generally have a positive relationship, and velocity has both a positive and negative relationship depending on the lags. The reason that some of the parameters have a negative relationship with particle number (e.g. fuel rate) is presumed to be caused by the close relationship (multicollinearity) of the operating bus characteristics. Fitting the model to another data set might include the same parameters with appreciably different values or signs.

Joint F-tests were used to determine the significance of each variable. Both models indicate that engine speed is the most significant, followed by fuel rate, acceleration and velocity. The engine parameters are more significant than the acceleration and speed, but they both added significant prediction power to the model.



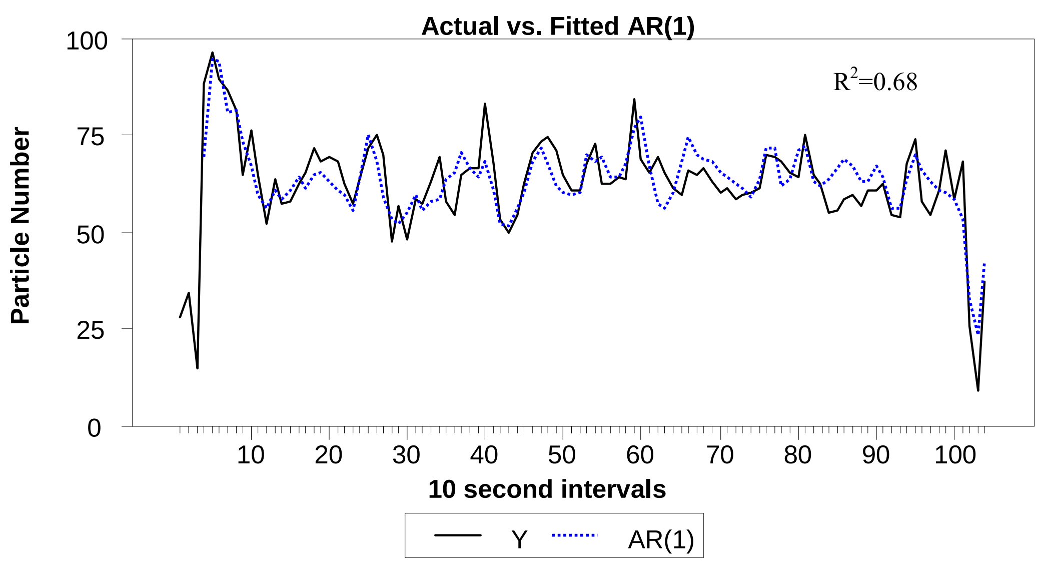
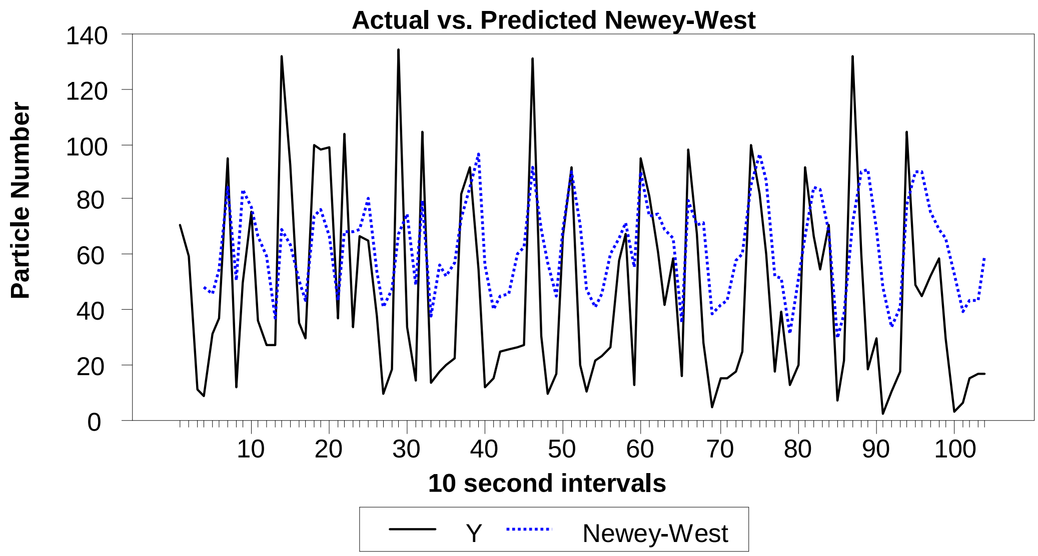


Figure 5 Fitted particle number concentration on the Enfield route for the Newey-West and AR(1) models compared to actual concentration (Y)

The fitted values of particle number concentrations are compared with the actual particle measurements for the two models in Figure 5. As shown, both models provide a reasonable fit to the fluctuations of particle concentrations. The Newey-West has a slightly higher degree of fit than the AR(1) model, with an R^2 value of 0.72 compared to 0.68. For practical purposes the differences in model fit is trivial.



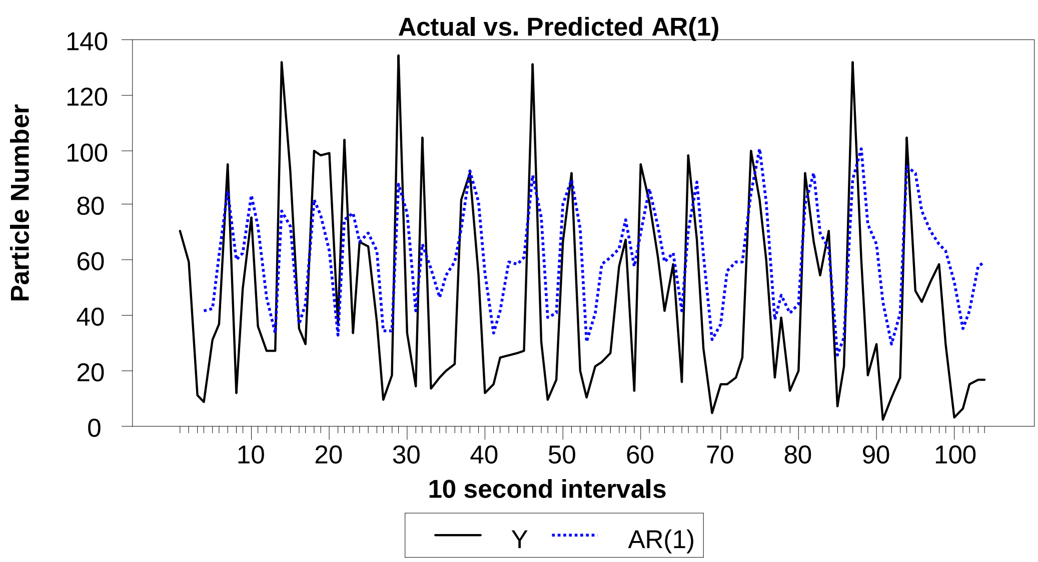


Figure 6 Predicted particle number concentration on the Farmington route compared to actual concentration (Y)

The robustness of the models was also evaluated by applying them to the Farmington bus route from the Holmén *et al.* study. The Farmington route has frequent stops and idling periods, typical of an urban transit bus route *(5)*. Figure 6 compares the Newey-West and AR(1) model predictions to real particle concentration measurements.

Both models fail to fully predict the high particle fluctuations. The Enfield route, from which the parameters for the model were estimated, had a smaller range of particle number concentrations, with very few observations of low particle number concentrations. Given the markedly varied driving and emitting conditions across facility types, particle number models should be developed specifically according to each facility type.

CHAPTER 5

CONCLUSIONS AND FUTURE RESEARCH

This research demonstrated that a sound emission model can be obtained from operating characteristics using econometric analysis. The econometric analysis techniques applied in this project have applicability to a wide range of emission models. For example, autocorrelation and nonstationarity problems will be encountered in almost all second-by-second emissions data, and methods to overcome these problems should be carefully evaluated. In this study, the Newey-West estimator in conjunction with OLS is shown to be an effective method to deal with autocorrelation and heteroscedasticity. By obtaining similar model values with an AR(1) FGLS regression, the Newey-West results are more convincing. The OLS Newey-West model developed from this study provides evidence that particle concentration is correlated with engine and vehicle parameters beyond the anticipated ten second lag. Both models confirmed that velocity and acceleration variables added benefit in predicting particle number concentration alongside engine characteristics: fuel rate and engine speed. Further, both models found that exhaust flow rate does not add predictive power to particle number concentration. When the models are applied to a route characterized by frequent stops and idling periods, both models failed to sufficiently forecast the more variable particle emission concentrations, particularly at low emission levels. This demonstrates that facility-specific modal emission models should be developed.

In future stages of my research, I anticipate conducting an analysis on the particle number emissions among different bus routes and bus technologies. The relationship and importance of the operating characteristics with particle emissions will most likely change by route, aftertreatment, engine type, and atmospheric conditions. Building econometric regression models may be an effective method to evaluate differences between these variables at a vehicle operation mode scale.

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