West Virginia University. Center for Alternative Fuels, Engines and Emissions.

Modeling Heavy-duty Vehicle Fuel Economy Based on Cycle Properties

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9/24/2009

Executive Summary

A methodology for predicting heavy-duty vehicle fuel economy during operation over "unseen" activity was developed based on fuel economy data gathered from operation measured from vehicles exercised over chassis dynamometer cycles and properties of those cycles. West Virginia University (WVU) Center for Alternative Fuels, Engines, and Emissions (CAFEE) heavy-duty chassis dynamometer data for over-the-road trucks and 40-foot transit buses were gathered from the CRC E55/59 program and the WMATA emission testing program, respectively. A linear model, a black box neural network model, and a commercial software model (PSAT) were used to predict either fuel economy in a distance traveled per volume of fuel consumed basis (miles per gallon) or fuel consumption inferred from CO_2 emissions mass rate (grams per second) basis. Most of the resources of this project were dedicated to the linear model. The methodology allowed for the prediction of fuel economy from vehicles operating on a number of different chassis dynamometer cycles based on relatively few experimental measurements. The results of the application of the linear model to a set of 56 heavy heavy-duty trucks operating over five different cycles showed that the use of average velocity and average positive acceleration as metrics produced the lowest average percentage error (less than 5%). The results of the application of the linear model to a set of five buses operating over 16 or 17 different cycles showed again that average velocity and average positive acceleration were suitable metrics to predict fuel economy with reasonable accuracy (less than 10% average percentage error). It was also found that baseline cycles must include Idle cycle, along with a relatively slow transient cycle and a relatively high speed cycle, preferably with an average velocity at or above the average velocity of the unseen cycle. Based on the results obtained with both data sets, it was recommended that the prediction be made in terms of CO_2 mass rate (g/s) and then convert to fuel economy (mpg). The results of the application of the black box neural network model and the commercial software model produced average percentage errors of the order of 10% and 4%, respectively. The main disadvantages of these alternative approaches with respect to the linear model were their inherent complexity (application difficulty) and the need to use continuous (second-by-second) data.

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1. Objective

The objective of this project was to develop a suitable methodology for predicting heavy duty vehicle fuel economy over an “unseen” speed-time cycle or during “unseen” on-road activity, based on fuel economy data from measured chassis dynamometer test cycles and properties of those cycles.

2. Introduction

This work was directed towards developing a methodology for inferring heavy-duty vehicle fuel economy during operation over “unseen” chassis dynamometer driving cycles based on fuel economy data which had been gathered from operation on known chassis dynamometer cycles and properties of those cycles. The methodology allowed for the prediction of fuel economy from vehicles operating on a number of different chassis dynamometer cycles based on relatively few experimental measurements. Through the course of this work, three different approaches were taken to define the best methodology to determine fuel economy for a vehicle exercised over a defined cycle. These approaches included a mathematical empirical-based linear model, a neural network-based model, and a whole vehicle system simulation model which incorporated fuel economy prediction.

In the modeling efforts presented herein, the West Virginia University (WVU) Center for Alternative Fuels, Engines, and Emissions (CAFEE) heavy-duty chassis dynamometer data were mined to identify test campaigns that could provide sufficient data to evaluate the three different modeling approaches. Two different test campaigns were identified and these campaigns were from the CRC E55/59 program and the WMATA emission testing program [1, 2]. The CRC E55/59 program data included 75 medium and heavy-duty diesel-fueled over-the-road trucks and tractors exercised over seven chassis dynamometer test cycles while the WMATA program included twelve transit buses exercised over as many as seventeen chassis dynamometer test cycles.

3. Background

3.1 Road Load Equation

Vehicle (or engine) fuel consumption depends on vehicle power demand as the vehicle is driven. The road load equation can be used to calculate the instantaneous power required to propel a vehicle. The power requirement for zero grade includes the rolling resistance which arises from the friction of the tires, the aerodynamic drag of the vehicle, and the inertial power required to accelerate the vehicle. Equation 1 shows the road load equation where P represents the propulsion power demanded by the vehicle at the drive wheels: this is vehicle power, not engine power; engine power would be greater than vehicle power because drive train efficiencies are less than 100%. In Equation 1 m is the mass of the vehicle, μ represents the coefficient of rolling resistance, g is the acceleration due to gravity, V is the instantaneous velocity, ρ is the ambient air density, A is the frontal cross sectional area of vehicle, C_D is the wind drag coefficient, and t is time.

$$P = \mu mgV + \frac{1}{2}\rho A C_D V^3 + mV\frac{dV}{dt} \qquad (1)$$

Note that road grade will also have an effect on vehicle power demand. However, chassis dynamometer testing is executed assuming level grade and road grade is excluded, with rare exception.

3.2 Cycle Properties (Metrics)

A chassis dynamometer test cycle is defined customarily as a speed versus time array, assuming level road. A cycle has a defined test duration and a target distance. There are additional means to describe a cycle using properties, or metrics, such as average velocity, standard deviation of velocity, average acceleration, and stops per unit distance. These metrics provide some information that the speed-time trace cannot give by itself. The most important metric to analyze fuel consumption is believed to be average velocity, because in Equation 1 velocity appears in each term. Average velocity is a robust indicator of the type of activity exhibited during a given cycle. A low average velocity can represent a very transient cycle similar to what is expected in city traffic while a high average velocity can represent a more steady behavior similar to what is expected in highway driving. Few vehicles travel at a steady, low speed, unless they are engaged in unusual vocational activity. The road load equation contains some cycle properties such as velocity and acceleration. However, the road load equation does not include other important properties such as stops per unit distance and percentage of time idling that can be taken into account in order to analyze fuel consumption.

Based on the rolling resistance and wind drag road load equation terms, it can be argued that fuel consumption will be higher if the vehicle is operated through a higher average speed cycle. However, a low average speed can represent a very transient cycle. Another metric should be introduced in order to account for transient behavior. Standard deviation of speed, average acceleration, and stops per unit distance are some of the examples of metrics that can account for transient behavior.

The main hypothesis of this research was that cycle metrics might be used to predict (with acceptable accuracy) the fuel economy of a vehicle exercised through an "unseen" speed-time trace. The road load equation suggests that average velocity should be one of the metrics to be used. Additional metrics may be selected to refine the model further to provide for higher fidelity in the results while minimizing the required amount of test data, or the number of chassis dynamometer cycles needed to be acquired.

3.3 Intensive and Extensive Properties

The data used in these models could be resolved by either using intensive or extensive cycle properties. Extensive properties depend on the size of the system; in this case factors such as cycle time length or distance traveled or integrated values of V^2 over the duration of the cycle. If a test cycle is run twice "back-to-back," and treated as one cycle, the values of its extensive properties would be doubled. On the other hand, intensive properties do not depend on the size (or length) of the system, and they are exemplified by properties such as average speed. The objective of this work was to predict fuel consumption on a mass rate (grams/second) or to predict fuel economy on a distance per unit volume of fuel consumed (miles/gallon). Both of these sets of units are intensive properties and hence, only intensive properties were used for the prediction. An equivalent approach would be to use extensive cycle properties to predict fuel consumption in mass (an extensive property), rather than mass rate. However, the desired units for this work are intensive and hence an intensive property set was selected.

Low average speed chassis dynamometer test cycles such as the Creep cycle or New York Bus cycle are relatively low distance cycles with relatively high amounts of idle time. These cycles translate into high fuel consumption values in volume per unit distance (gallons/mile) units. Idle cycles are more problematic on a volume per unit distance because, by definition, this cycle would have an infinite value of fuel consumption since the distance traveled is zero. As will be shown below, it is possible to convert from one set of fuel economy, or consumption, units to another set of units through knowledge of the properties of the cycle. As such, CO_2 emissions mass rate, in grams per second, is the desired intensive property selected to measure fuel consumption. If a volume-specific fuel economy, miles per gallon value would be needed, a conversion factor can be used, provided that the carbon content of the petroleum fuel is estimated or known.

4. Procedure

The main features of the three techniques used to predict fuel economy for heavy duty vehicle are summarized below.

4.1 Linear Model

The Linear Model approach involved identifying the most important intensive metrics of a cycle and developing a technique which calculates the CO_2 mass rate emissions for a "new" cycle based on CO_2 mass rate emissions from actual chassis dynamometer test cycle data using those selected metrics as weighting factors. Using this technique, heavy-duty vehicles of a chosen category can be tested using a limited number of chassis dynamometer test cycles, and the data from those tests may be used to project emissions from an unseen cycle in a wide envelope, within certain bounds. This prediction approach avoids the use of continuous (second by second) data and the predictions are made *a priori* based on the relative cycle statistics. No regression is required. This simple method does not require training a model as is needed in neural network modeling or the need for detailed component models as is needed in vehicle system simulation modeling.

4.2 Commercial Software Model

Models such as ADVISOR or PSAT may be used to predict the fuel economy of a vehicle, by assembling models of components of the vehicle, and employing estimates for losses, efficiency of components, and vehicle inertia, under constraint of driver behavior. It is difficult to use a pure modeling approach for actual or comparative fuel consumption prediction using this approach because a great deal of information is required for each vehicle (such as drivetrain components), and because it is increasingly difficult to verify that modeled control strategy (particularly for hybrid vehicles) reflects the in-use control strategy. However, models of this kind may be used readily to translate performance from a small set of real-world tests to an unseen cycle and accuracy is expected to be good.

4.3 Neural Network - Black Box Model

Another powerful tool that can be used to model fuel economy involves training of a neural network, or other non-classical models, using second by second data, so that the neural network can then predict second-by-second performance on unseen cycles. Training the neural network using continuous emissions data requires some skill because one must account for delay and diffusion of data during measurement, and one must avoid overtraining by selecting input variables and network architecture suitably. Training should be done with data containing varied vehicle behavior that encompasses the range of vehicle operation in the unseen cycle. Continuous data are required for this approach.

5. Linear Model Approach

WVU has identified and developed a method for predicting emissions data for transient vehicle activity (such as a chassis dynamometer test cycle) based on information from other measured chassis dynamometer test cycles. The technique was presented in a 2004 paper by Taylor et al. [3]. This approach involves identifying the most important properties (metrics) of a cycle (such as average speed, standard deviation of speed, and percent idle) and developing a technique which proportions emissions for an “unseen” cycle based on emissions from real-world cycle data using those metrics for weighting.

The main assumption in this modeling approach is that for a given vehicle, fuel consumption over an “unseen” cycle will be a linear combination of its fuel consumption over other baseline cycles. Each baseline cycle will contribute to a percentage of the fuel consumption of the unseen cycle. Fuel consumption depends on cycle properties so the weighing factors (or fractional contributions) of the different baseline cycles will be obtained based on the selected cycle properties. A set of linear equations based on cycle properties is posed in order to determine the weighting factors of each baseline cycle to then estimate the “unseen” cycle. In each case, the predicted fuel economy (or CO_2 emissions) would be a weighted summation of the fuel economy (or CO_2 emissions) from the baseline cycles, with the weighting coefficients constrained to sum to unity.

The number (N) of baseline test cycles determines the number of simultaneous equations and, hence, the number of properties that can be used. One of the equations will always constrain the sum of the coefficients to be equal to one, so there will be N-1 properties that are used to solve the N simultaneous equations. The following section explains the method more clearly using a step by step example.

5.1 Example

Assume that fuel economy measurements for three different test cycles are available and one wants to estimate fuel economy for a fourth, different cycle. The three measured cycles are termed the “baseline cycles” and the predicted cycle is termed “unseen cycle.” The baseline cycles form the basis to estimate fuel economy for the unseen cycle. Each baseline cycle will have a weighting factor that defines the relative proportion of that cycle to the unseen cycle in terms of the metrics used. It is expected that these weighting factors also can be used to then estimate the unseen cycle fuel economy. Two cycle properties should be used because the number of baseline cycles is three. Table 1 shows two properties (average velocity and average acceleration) for three baseline cycles (termed Idle, Transient, and Cruise) and one unseen cycle (UDDS cycle). The objective is to use information from the three baseline cycles to predict fuel economy from the UDDS cycle. Note that metrics other than average velocity and average acceleration could have been chosen to perform the analysis which is presented below.

Table 1. Metrics and measured fuel economy for three baseline cycles and one "unseen" cycle.

Cycle		Average Velocity (mph)	Average Acceleration (mph/s)	Measured Fuel Economy (mpg)
Baseline cycles	Idle	0.00	0.00	0.00
	Transient	14.92	0.29	3.85
	Cruise	39.87	0.12	6.58
"unseen" cycle	UDDS	18.83	0.32	?

The next step is to pose a set of three simultaneous equations, based on the selected cycle properties, to calculate the weights of each baseline cycle to the "unseen" cycle. The three unknowns are the weighting factor for each baseline cycle. The equation set is shown in Equations 2, 3, and 4. The first two equations are linear combinations using the two different metrics. The first equation uses average velocity, the second equation uses average acceleration, and the third equation constrains the weights to sum to one.

$$w^{idle} speed^{idle} + w^{trans} speed^{trans} + w^{cruise} speed^{cruise} = speed^{UDDS} \qquad \textbf{(2)}$$

$$w^{idle} accel^{idle} + w^{trans} accel^{trans} + w^{cruise} accel^{cruise} = accel^{UDDS} \qquad \textbf{(3)}$$

$$w^{idle} + w^{trans} + w^{cruise} = 1 \qquad \textbf{(4)}$$

Replacing numerical values from Table 1 in Equations 2, 3, and 4 results with the following equation set:

$$w^{idle}\,(0) + w^{trans}(14.92) + w^{cruise}(39.87) = 18.83 \qquad \textbf{(5)}$$

$$w^{idle}(0) + w^{trans}(0.29) + w^{cruise}(0.12) = 0.32 \qquad \textbf{(6)}$$

$$w^{idle} + w^{trans} + w^{cruise} = 1 \qquad \textbf{(7)}$$

The next step is to solve the simultaneous equations to obtain the weighting factors. Note that this solution is unique and for this example is:

$$w^{idle} = -0.1446 \qquad \textbf{(8)}$$

$$w^{trans} = 1.0744 \qquad \textbf{(9)}$$

$$w^{cruise} = 0.0702 \qquad \textbf{(10)}$$

Finally, the weighting factors are used to calculate fuel economy for the “unseen” cycle:

$$mpg^{UDDS} = w^{idle} mpg^{idle} + w^{trans} mpg^{trans} + w^{cruise} mpg^{cruise} \quad \textbf{(11)}$$

$$mpg^{UDDS} = -0.1446\, mpg^{idle} + 1.0744\, mpg^{trans} + 0.0702\, mpg^{cruise} \quad \textbf{(12)}$$

$$mpg^{UDDS} = -0.1446\,(0) + 1.0744(3.85) + 0.0702(6.58) \quad \textbf{(13)}$$

$$mpg^{UDDS} = 4.59\, mpg \quad \textbf{(14)}$$

The negative coefficient for the Idle cycle suggests that Transient and Cruise cycles already contain more Idle than the UDDS cycle (less Idle should be considered in the UDDS than in the weighted active modes Transient and Cruise cycles). The Transient term coefficient equal to approximately one (1.0744) suggest that the UDDS is closest to the Transient mode and the low value for the Cruise coefficient (0.0702) indicates that a relatively small portion of UDDS is at cruise conditions. In this example, the weight coefficient for Idle, in effect, is not being used due to the zero value of fuel economy (mpg) for the Idle cycle. Regardless of the mass of fuel used per hour of Idling, the Idle contribution will be the same. It is recommended that one would predict fuel consumption using CO_2 mass rate (g/s) instead of fuel economy (in mpg) to avoid negating the Idle information.

5.2 Geometric Explanation

The previous example has an alternative geometric explanation. Solving a system of three equations and three unknowns as shown in the previous example is equivalent to finding the equation of a plane in a three dimensional space. Figure 1 shows a geometric representation of the previous example. In this case the dimensions of the three dimensional space are average velocity, average acceleration, and fuel economy. Information for each baseline cycle represents a point in that three dimensional space. Once the three points have been specified, a plane that crosses the three points (unless the points are collinear) can be defined. This plane is unique because one and only one plane can cross through these three points. The plane can be used to predict other cycle’s fuel economy *a priori*, just knowing these new cycle’s properties (average velocity and average acceleration in this example). This modeling approach simplifies the real world surface (which may be curvilinear) to a plane, using minimum information. The prediction may use extrapolation (points on the plane but outside the triangle shown) but as with other linear models, extrapolation should be exercised with caution.

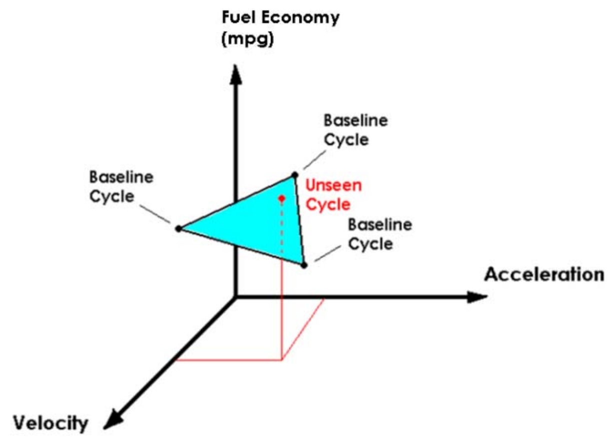


Figure 1. Geometric interpretation of the linear model method.

5.3 Predicted Properties

As discussed above, CO_2 mass rate emissions (g/s) or fuel economy (mpg) could be estimated in the model and then the other property calculated. Conversion between mass rate (g/s) and fuel economy (mpg) is based on average speed. Equation 15 shows the U.S. Environmental Protection Agency recommended practice to perform the calculation from CO_2 mass rate to fuel consumption [10]. This equation assumes diesel carbon content per gallon of 2,778 grams and an oxidation factor of 0.99 (99 percent of the carbon in the fuel is eventually oxidized, while 1 percent remains un-oxidized). Equation 16 shows the calculation from fuel consumption volumetric rate (gal/s) to fuel economy (mpg). This calculation is cycle dependent because cycle average speed is used in the conversion. Note also that for the Idle cycle, fuel economy (mpg) is zero. It is emphasized again that CO_2 mass rate (g/s) should be used instead of fuel economy (mpg) to include idle information in the model.

$$Fuel\ Consumption\ \left(\frac{gal}{s}\right) = \frac{CO_2\left(\frac{g}{s}\right)}{10084} \qquad \textbf{(15)}$$

$$Fuel\ Economy\ (mpg) = \frac{Average\ Speed\ (mph)}{Fuel\ Consumption\ \left(\frac{gal}{s}\right)\times 3600} \qquad \textbf{(16)}$$

6. Linear Model Application - Truck Data

The linear model was applied to two different heavy duty vehicle types. These types included heavy-duty trucks and transit buses. This section summarizes the linear model application to the truck data. Chassis dynamometer data for 56 heavy heavy-duty trucks operating at a nominal 56,000lbs inertial mass were used. The data used were gathered as part of the Coordinating Research Council E-55/E59 program, which was created to characterize heavy-duty trucks emissions in California. It is noted that the other 19 vehicles in the E-55/59 program were medium-duty (and not tested at the 56,000lbs mass) and or gasoline-fueled vehicles and were excluded in this analysis. That is, only the class 8 heavy-duty trucks incorporating diesel engines were modeled in this work.

6.1 Cycles Used

California Air Resources Board created a four-mode speed versus time heavy-heavy duty diesel truck vehicle chassis test schedule (HHDDT) based on data gathered from prior truck activity studies [12, 13]. Idle, Creep, Transient, and Cruise of the HHDDT schedule were used as baseline cycles and the UDDS (Urban Dynamometer Cycle Schedule) was used as the “unseen” cycle. The UDDS cycle includes behavior that represents both freeway and non-freeway operation and is located in the Code of Federal Regulations [4]. Since actual UDDS data were available, the UDDS was considered a validation cycle. Predicted and measured UDDS data could be compared. Figure 2 shows the test cycles used as baseline cycles and Figure 3 shows the test cycle used for validation.

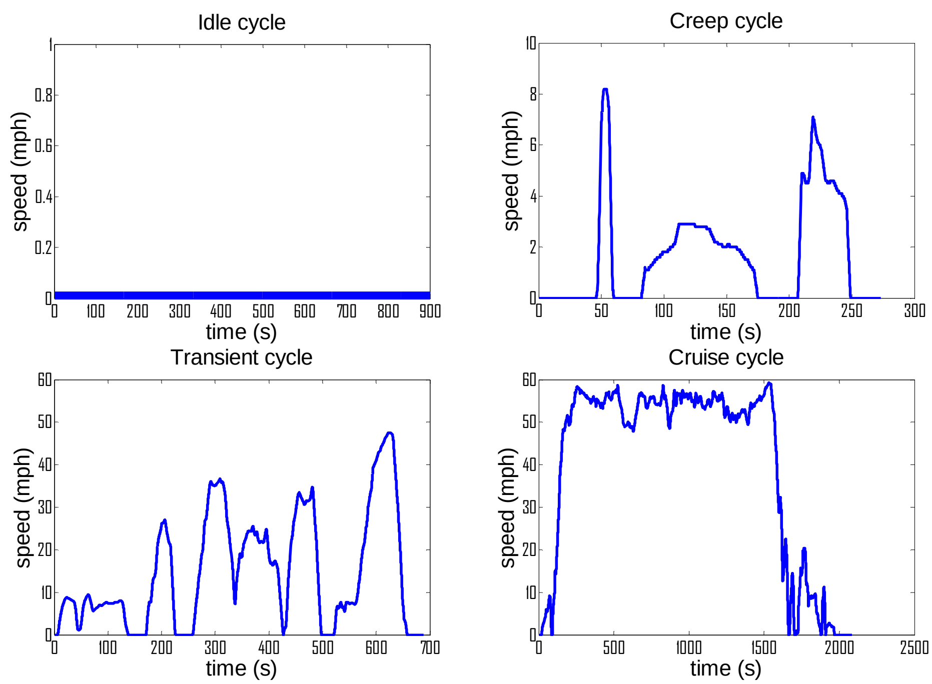


Figure 2. Baseline cycles used with truck data set.

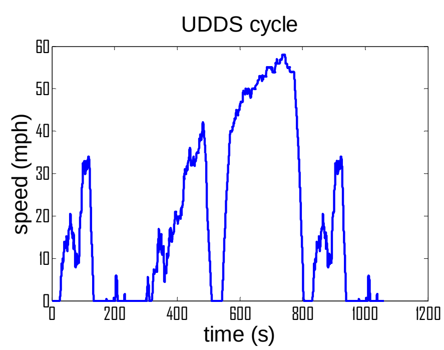


Figure 3. Validation cycle used with truck data set.

6.2 Metrics Used

Nine different metrics were evaluated with this data set. Table 2 shows metrics values for the five cycles used. Equations 17 to 25 show the formulation of the problem used to calculate the metrics. It is noted that additional metrics could be defined but from the authors' experience these metrics presented in Table 2 best represented in-use vehicle activity.

Table 2. Metrics values for Truck data.

Metric	Baseline Cycles				Validation C.
	Idle	Creep	Transient	Cruise	UDDS
Average Velocity (mph)	0.00	1.64	14.92	39.87	18.83
Standard Deviation of Velocity (mph)	0.00	2.02	13.44	22.01	19.82
Average of Squared Velocity (mph^2)	0.00	6.76	403	2074	747
Average of Cubed Velocity (mph^3)	0.00	34.78	13044	111410	33992
Average Acceleration (mph/s)	0.00	0.07	0.29	0.12	0.32
Inertial Power (mph^2/s)	0.00	0.23	5.06	3.86	6.41
Average of Squared Acceleration (mph^2/s^2)	0.00	0.80	0.86	0.26	1.80
Stops per mile (stops/mile)	0.00	24.20	1.80	0.30	2.50
Percentage Idle (%)	100.00	42.30	16.30	8.00	33.40

Average Velocity

$$\bar{V} = \frac{\sum_{i=1}^{n} V_i}{n} \quad \textbf{(17)}$$

Standard Deviation of Velocity

$$\sigma_V = \sqrt{\frac{\sum_{i=1}^{n}(V_i - \bar{V})^2}{n-1}} \quad \textbf{(18)}$$

Average of Squared Velocity

$$\overline{V^2} = \frac{\sum_{i=1}^{n} V_i^2}{n} \quad \textbf{(19)}$$

Average of Cubic Velocity

$$\overline{V^3} = \frac{\sum_{i=1}^{n} V_i^3}{n} \quad \textbf{(20)}$$

Average Acceleration

$$\frac{\partial V}{\partial t} = \frac{\sum_{i=1}^{n} \frac{V_{i+1}-V_i}{\nabla t}}{n} \text{ when } V_{i+1} > V_i \quad \textbf{(21)}$$

A Savitsky-Golay filtering method of 2nd degree over 21 data points (2.1 seconds) was applied to the speed time trace before calculating acceleration. This method computes a local polynomial regression on the input data and is preferred over other techniques such as moving averages because it tends to preserve features of the distribution such as relative maxima, minima and width. Acceleration was calculated with a central differences scheme. Actual speed-time traces were used. Only positive values were taken into account since it was assumed that the engine does not consume fuel when decelerating. Note that the denominator in the formula is the total number of data points, not the number of data points with positive acceleration.

Average Inertial Power

$$\overline{V\frac{\partial V}{\partial t}} = \frac{\sum_{i=1}^{n} V_i \frac{V_{i+1}-V_i}{\nabla t}}{n} \text{ when } \frac{\partial V}{\partial t} > 0 \quad \textbf{(22)}$$

Average of Squared Acceleration

$$\overline{\left(\frac{\partial V}{\partial t}\right)^2} = \frac{\sum_{i=1}^{n}\left(\frac{\partial V}{\partial t}\right)_i^2}{n} \text{ when } \frac{\partial V}{\partial t} > 0 \quad \textbf{(23)}$$

Stops per Mile

$$\frac{Stops}{mile} = \frac{number\ of\ stops}{distance\ traveled\ (miles)} \quad \textbf{(24)}$$

A velocity value below 0.5 miles per hour was counted as a stop to account for the resolution in the chassis dynamometer data acquisition system. Stop duration was not taken into account, for example, if the vehicle remained below 0.5 mph during a long period it was counted as only one stop. The stop analysis was done without filtering of the speed-time trace.

Percentage Idle

Any data point with velocity below 0.5 mph was considered to be an idle event. The idle analysis was done without filtering of the speed-time trace.

$$\%\ Idle = \frac{number\ of\ data\ points\ below\ 0.5\ mph}{total\ number\ of\ data\ points} \quad \textbf{(25)}$$

6.3 Cases Used

Sixty-one cases were evaluated, including five different combinations of baseline cycles and a number of metrics. Table 3 show the cases used. Cycle averaged velocity was used in all cases as a metric. Cases 1 to 4 have eight possible combinations (velocity and another metric) and case 5 has 28 possible combinations (velocity and two other metrics).

Table 3. Cases used truck data

CASE ID	Baseline cycles used	# of metrics used	Metrics used
0	Transient and Cruise	1	Velocity only
1	Idle, Transient and Cruise	2	Velocity + 1 metric (all combinations)
2	Creep, Transient and Cruise	2	
3	Idle, Creep and Cruise	2	
4	Idle, Creep and Transient	2	
5	Idle, Creep, Transient and Cruise	3	Velocity + 2 metrics (all combinations)

6.4 Goodness of Fit Criteria

Four criteria were selected to evaluate the goodness of fit between the measured and predicted UDDS data: average percentage error (Equation 26 where X_p are predicted values and X_e are experimental values), maximum absolute error, average absolute error (Equation 27 where X_p are predicted values and X_e are experimental values), and R^2 correlation coefficients between the measured and predicted values. Note that R^2 could be a misleading measure when data are clustered, as may be the case with a fuel economy measure. The recommended goodness of fit criterion in this work was average percentage error or average absolute error but the other criteria are presented below as well.

$$\text{Average \% error} = \frac{1}{n}\sum_{i=1}^{n}\frac{\left|x_p - x_e\right|_i}{(x_e)_i} \times 100 \qquad \textbf{(26)}$$

$$\text{Average absolute error} = \frac{1}{n}\sum_{i=1}^{n}\left|x_p - x_e\right|_i \qquad \textbf{(27)}$$

6.5 Truck Data Results and Analysis

Tables 4 and 5 show the summary of prediction results for CO_2 (g/s) and fuel economy (mpg), respectively. The data were organized based on average percentage error values over 56 predictions (one prediction per truck). Note that not all of the cases worked well. Some metrics yielded more suitable than others to translate fuel economy or fuel consumption among cycles. Also, some baseline cycle combinations were better than others when trying to predict the validation cycle. Note that 27 cases were below 10% error for CO_2 mass rate (g/s) and 16 cases were below 10% error for fuel economy (mpg). This could be because of the loss of information when using the Idle cycle fuel consumption (mpg) data discussed above. Tables 6 and 7 show more detail about the four lowest error predictions for CO_2 (g/s) and fuel consumption (mpg), respectively. Figures 4 and 5 display scatter plots of the average prediction error showing the cases where the average percentage error was lower than 12%. The best combination of accuracy and economy (in terms of number of baseline cycles used) was obtained using Idle, Transient, and Cruise as baseline cycles with average velocity and average acceleration as metrics. To incorporate four baseline cycles into the analysis, the best metric to add to the model would be the number of stops per unit distance (stops/mile). It is worth mentioning that the use of average velocity as the only metric with the Transient and Cruise baseline cycles produced good results for CO_2 (g/s) and was even better in terms of economy (number of metrics used) than the recommended combination of average velocity and acceleration. However, the use of this metric alone should be avoided because two cycles with similar average velocity can represent very different type of activity and very different fuel consumption patterns. Use of an additional metric is recommended to account for the degree of transient behavior of the cycle.

Another important issue is that the results were very similar for fuel economy (mpg) and for CO_2 (g/s) even with the fuel economy prediction ignoring the weighting coefficient for the Idle cycle. This could be due to the high similarity between the Transient cycle and UDDS cycle, and the fact that only a small fraction of the fuel was consumed during idling portions of each cycle. Table 8 shows the weighting factors sensitivity to the addition/subtraction of cycles and metrics. Note that the average percentage error does not show a significant change for fuel economy but the error goes to more than 8% when using velocity alone as a metric with the Creep and Transient cycle. Further insight in this topic will be gained in the next section of this report.

Figures 6 and 7 show the results using the recommended baseline cycles and metrics for CO_2 mass rate and fuel economy, respectively. Idle, Transient, and Cruise cycles with average velocity and average acceleration as metrics were used to predict the UDDS cycle for 56 trucks. A parity plot between measured and predicted values is shown, as well as the resulting equation for prediction. Note that the weighting factors are the same for CO_2 and fuel economy prediction (using the same metrics and the same baseline cycles), but the Idle cycle information is lost in the fuel economy prediction because of the zero economy value for the Idle cycle. Figure 8 shows the CO_2 mass rate (g/s) predictions shown in Figure 6, converted to fuel economy (mpg) using equations 15 and 16. It is recommended that the prediction be made in terms of CO_2 mass rate (g/s) or the equivalent units of g/s of fuel mass flow. One may then compute fuel economy (mpg) using average cycle speed.

As in the previous example, the Transient cycle weighting factor was nearly one, and the Idle cycle weighting factor was negative. These coefficients suggest that the UDDS is closest to the Transient cycle and that less idle should be considered in the UDDS than in the weighted active modes (Transient and Cruise cycles).

Table 4. CO_2 mass rate prediction results.

Metrics Used	Case Used	Average Percent Error (%)	Maximum Error (CO_2)	Average Error (CO_2)	R^2
Velocity, Acceleration, Stops/mile	5	4.29	2.00	0.52	0.82
Velocity , Acceleration	1	4.36	2.02	0.52	0.82
Velocity	0	4.36	2.43	0.54	0.83
Velocity , Acceleration	2	4.89	2.16	0.58	0.81
Velocity , Stops/mile	2	5.49	2.69	0.68	0.83
Velocity, Acceleration, Acceleration^2	5	6.68	3.89	0.82	0.65
Velocity, Acceleration, %Idle	5	7.13	2.61	0.84	0.78

Velocity, Velocity^3, Velocity^2	5	7.31	3.13	0.90	0.80
Velocity , Acceleration^2	4	7.65	3.09	0.90	0.73
Velocity, Acceleration, Inertial Power	5	7.96	2.75	0.94	0.76
Velocity, Inertial Power, %Idle	5	8.01	2.81	0.95	0.77
Velocity, Velocity^3, %Idle	5	8.15	3.20	1.00	0.82
Velocity , Inertial Power	2	8.21	3.02	0.96	0.80
Velocity , Stops/mile	4	8.26	3.11	0.97	0.80
Velocity , Inertial Power	4	8.38	3.11	0.98	0.80
Velocity, Velocity^2, Inertial Power	5	8.42	5.84	1.04	0.42
Velocity , Inertial Power	1	8.44	3.14	0.99	0.80
Velocity, Inertial Power, Stops/mile	5	8.45	3.15	0.99	0.80
Velocity ,Velocity^3	1	8.68	3.25	1.06	0.82
Velocity, Velocity^2, %Idle	5	8.71	3.29	1.07	0.82
Velocity, Velocity^3, Stops/mile	5	8.82	3.26	1.08	0.82
Velocity ,Velocity^3	2	9.06	3.28	1.11	0.82
Velocity , Velocity^2	1	9.43	3.36	1.15	0.82
Velocity, Inertial Power, Acceleration^2	5	9.47	3.56	1.11	0.74
Velocity , %Idle	4	9.47	3.13	1.11	0.77
Velocity, Velocity^3, Inertial Power	5	9.49	7.19	1.19	0.30
Velocity, Velocity^2, Stops/mile	5	9.65	3.39	1.18	0.82
Velocity , Velocity^2	2	10.12	3.44	1.23	0.82
Velocity , Acceleration	4	10.36	3.63	1.22	0.71
Velocity , Stops/mile	1	11.69	3.82	1.37	0.78
Velocity , Std.Dev.Velocity	4	11.80	7.50	1.47	0.23
Velocity, Std.Dev.Velocity, Inertial Power	5	13.33	5.40	1.59	0.51
Velocity, Velocity^3, Acceleration^2	5	13.49	5.43	1.64	0.54
Velocity , %Idle	1	13.59	4.01	1.65	0.80
Velocity, Stops/mile, %Idle	5	15.57	4.31	1.89	0.78
Velocity, Velocity^2, Acceleration^2	5	17.33	6.21	2.10	0.46
Velocity , Std.Dev.Velocity	3	19.42	13.57	2.40	0.07
Velocity , Velocity^2	4	19.47	11.69	2.35	0.24
Velocity, Velocity^3, Acceleration	5	19.51	8.86	2.37	0.20
Velocity ,Velocity^3	3	20.30	9.30	2.46	0.17
Velocity , Acceleration	3	20.42	9.20	2.48	0.18
Velocity, Std.Dev.Velocity, Acceleration^2	5	20.96	5.72	2.48	0.73
Velocity , Velocity^2	3	21.65	8.19	2.61	0.25
Velocity , Std.Dev.Velocity	1	22.96	5.99	2.72	0.74
Velocity , Acceleration^2	3	22.99	7.37	2.77	0.35
Velocity, Std.Dev.Velocity, Stops/mile	5	23.08	6.01	2.73	0.74
Velocity , %Idle	3	25.71	5.81	3.10	0.56
Velocity , Std.Dev.Velocity	2	26.07	6.41	3.09	0.72

Velocity , Stops/mile	3	26.24	5.96	3.16	0.55
Velocity, Std.Dev.Velocity, %Idle	5	29.41	6.86	3.49	0.67
Velocity ,Velocity^3	4	31.98	21.60	3.89	0.09
Velocity , Acceleration^2	1	33.52	8.02	3.98	0.70
Velocity, Acceleration^2, Stops/mile	5	35.12	8.32	4.17	0.69
Velocity , %Idle	2	37.64	8.12	4.52	0.19
Velocity, Velocity^2, Acceleration	5	43.46	17.72	5.25	0.01
Velocity, Velocity^3, Std.Dev.Velocity	5	71.85	38.05	8.73	0.00
Velocity, Std.Dev.Velocity, Acceleration	5	88.64	33.27	10.62	0.17
Velocity , Acceleration^2	2	106.01	21.31	12.64	0.54
Velocity , Inertial Power	3	160.07	111.49	19.97	0.01
Velocity, Acceleration^2, %Idle	5	808.14	162.68	96.50	0.38
Velocity, Std.Dev.Velocity, Velocity^2	5	1402.10	633.08	169.29	0.03

Table 5. Fuel economy (mpg) prediction results.

Metrics Used	Case Used	Average Percent Error (%)	Maximum Error (mpg)	Average Error (mpg)	R^2
Velocity , Acceleration	1	4.59	0.67	0.20	0.82
Velocity , Acceleration	2	4.83	0.57	0.21	0.82
Velocity , Inertial Power	2	4.94	0.60	0.22	0.79
Velocity, Acceleration, Stops/mile	5	4.98	0.70	0.21	0.82
Velocity	0	5.02	0.55	0.22	0.84
Velocity , Stops/mile	2	5.13	0.56	0.23	0.84
Velocity ,Velocity^3	2	5.40	0.58	0.24	0.83
Velocity , Velocity^2	2	5.48	0.59	0.24	0.83
Velocity , Std.Dev.Velocity	2	6.65	0.93	0.29	0.65
Velocity , Inertial Power	4	6.90	0.80	0.30	0.80
Velocity, Velocity^3, Stops/mile	5	7.94	0.78	0.36	0.83
Velocity , %Idle	2	8.43	1.02	0.38	0.51
Velocity, Velocity^2, Stops/mile	5	8.70	0.83	0.39	0.82
Velocity ,Velocity^3	1	9.81	0.90	0.44	0.82
Velocity , Inertial Power	1	9.82	0.91	0.43	0.80
Velocity , Stops/mile	4	10.00	0.92	0.44	0.80
Velocity, Inertial Power, Stops/mile	5	10.20	0.93	0.44	0.80
Velocity , Velocity^2	1	10.57	0.95	0.48	0.82
Velocity , %Idle	3	10.75	1.02	0.49	0.66
Velocity , Stops/mile	1	13.61	1.11	0.60	0.78
Velocity, Stops/mile, %Idle	5	14.21	1.19	0.64	0.77
Velocity , %Idle	1	14.92	1.23	0.68	0.78

Velocity, Velocity^2, %Idle	5	16.77	1.33	0.76	0.79
Velocity, Velocity^3, %Idle	5	16.99	1.34	0.77	0.79
Velocity , Acceleration^2	2	18.07	2.45	0.80	0.29
Velocity, Acceleration, %Idle	5	22.69	1.64	1.02	0.69
Velocity, Inertial Power, %Idle	5	23.11	1.66	1.04	0.68
Velocity , %Idle	4	23.80	1.70	1.07	0.65
Velocity , Stops/mile	3	24.83	1.85	1.12	0.52
Velocity, Std.Dev.Velocity, Stops/mile	5	24.94	1.89	1.10	0.73
Velocity , Std.Dev.Velocity	1	26.05	1.95	1.15	0.73
Velocity, Acceleration, Inertial Power	5	28.75	1.99	1.29	0.61
Velocity, Velocity^3, Velocity^2	5	30.34	2.12	1.36	0.64
Velocity, Std.Dev.Velocity, %Idle	5	31.80	2.30	1.42	0.39
Velocity, Acceleration^2, Stops/mile	5	37.08	2.71	1.65	0.67
Velocity , Acceleration^2	1	37.86	2.75	1.68	0.68
Velocity, Std.Dev.Velocity, Acceleration^2	5	43.97	3.05	1.95	0.73
Velocity , Acceleration	4	45.71	2.97	2.04	0.30
Velocity, Inertial Power, Acceleration^2	5	49.72	3.33	2.20	0.74
Velocity , Acceleration^2	4	50.97	3.40	2.26	0.74
Velocity, Acceleration, Acceleration^2	5	57.07	3.70	2.52	0.72
Velocity, Velocity^3, Acceleration^2	5	60.73	3.88	2.69	0.70
Velocity, Velocity^2, Acceleration^2	5	62.59	3.97	2.77	0.68
Velocity , Acceleration^2	3	65.35	4.10	2.89	0.66
Velocity , Velocity^2	3	102.41	6.40	4.54	0.62
Velocity, Std.Dev.Velocity, Inertial Power	5	131.90	8.43	5.85	0.64
Velocity, Velocity^2, Inertial Power	5	139.03	8.41	6.19	0.15
Velocity, Velocity^3, Acceleration	5	142.47	8.89	6.32	0.60
Velocity , Acceleration	3	148.27	9.25	6.57	0.59
Velocity ,Velocity^3	3	152.99	9.54	6.78	0.59
Velocity, Velocity^3, Inertial Power	5	185.66	11.25	8.26	0.24
Velocity , Std.Dev.Velocity	4	225.89	14.17	10.03	0.58
Velocity , Velocity^2	4	252.09	15.27	11.21	0.29
Velocity, Velocity^2, Acceleration	5	294.59	18.15	13.07	0.52
Velocity, Acceleration^2, %Idle	5	341.75	31.76	15.02	0.00
Velocity , Std.Dev.Velocity	3	346.92	21.57	15.41	0.54
Velocity ,Velocity^3	4	506.02	30.91	22.50	0.38
Velocity, Std.Dev.Velocity, Acceleration	5	544.22	32.90	24.18	0.34
Velocity, Velocity^3, Std.Dev.Velocity	5	820.60	50.52	36.45	0.48
Velocity , Inertial Power	3	2835.30	175.90	126.03	0.48
Velocity, Std.Dev.Velocity, Velocity^2	5	12207.33	746.53	542.24	0.43

Table 6. Best predictions for CO_2 mass rate.

Baseline Cycles Used	Metric(s) Used	Average % Error	Average Error (g/s)	Max. Error (g/s)	R^2
Idle, Creep, Transient and Cruise	Velocity, Acceleration and Stops/mile	4.29	0.52	2.00	0.82
Idle, Transient and Cruise	Velocity and Acceleration	4.36	0.52	2.02	0.82
Transient and Cruise	Velocity	4.36	0.54	2.43	0.83
Creep, Transient and Cruise	Velocity and Acceleration	4.89	0.58	2.16	0.81

Table 7. Best prediction for fuel economy (mpg).

Baseline Cycles Used	Metrics Used	Average % Error	Average Error (mpg)	Max. Error (mpg)	R^2
Idle, Transient and Cruise	Velocity and Acceleration	4.59	0.20	0.67	0.82
Creep, Transient and Cruise	Velocity and Acceleration	4.83	0.21	0.57	0.82
Creep, Transient and Cruise	Velocity and Inertial Power	4.94	0.22	0.60	0.79
Idle, Creep, Transient and Cruise	Velocity, Acceleration and Stops/mile	4.98	0.21	0.70	0.82

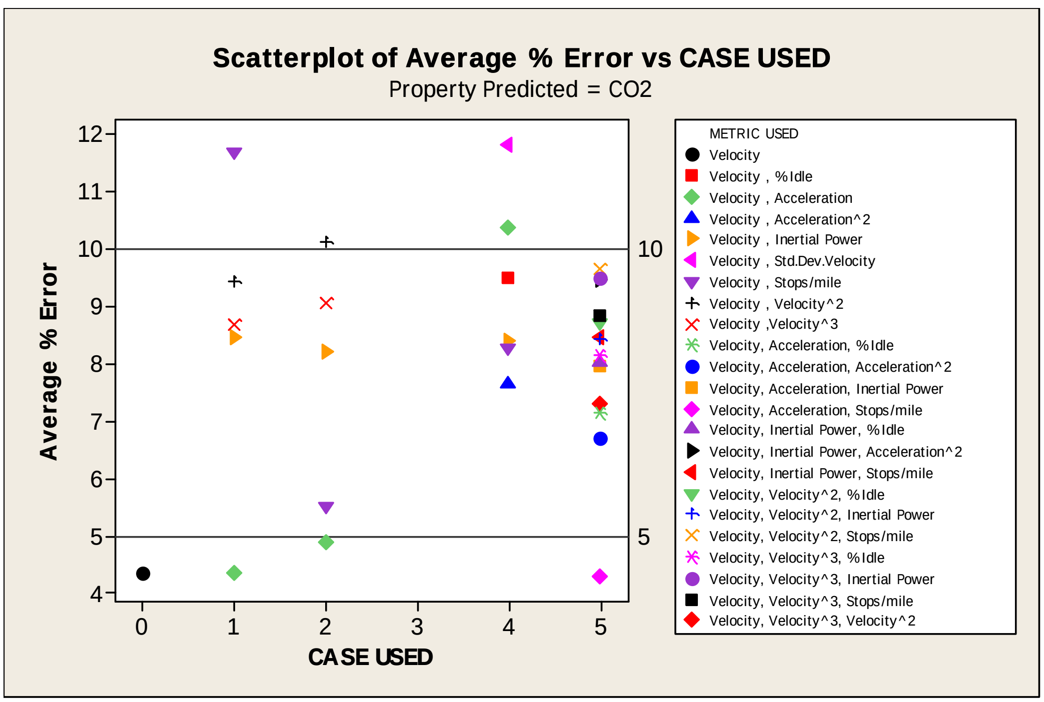


Figure 4. Scatter plot of average percent error for CO_2.

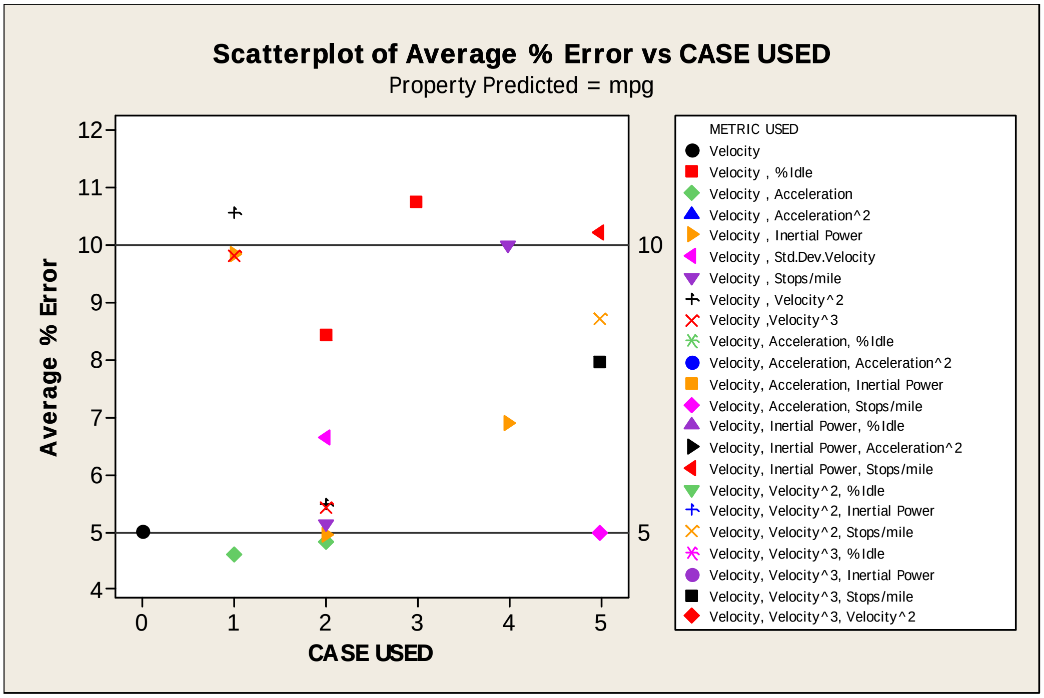
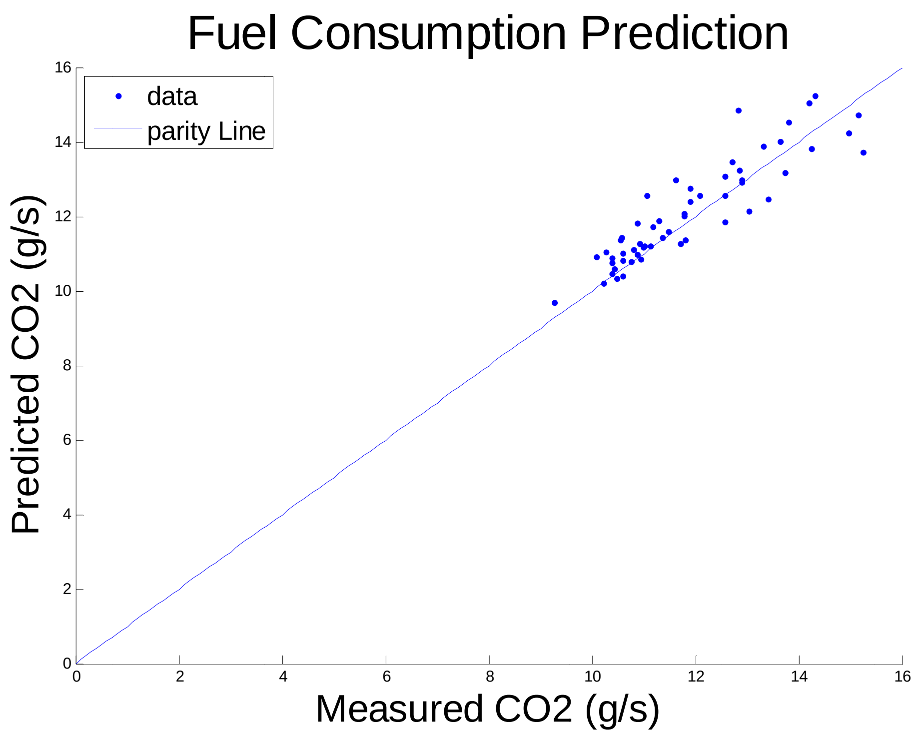


Figure 5. Scatter plot of average percent error for fuel economy (mpg).

Table 8. Weighting factors sensitivity to changes in baseline cycles and metrics used.

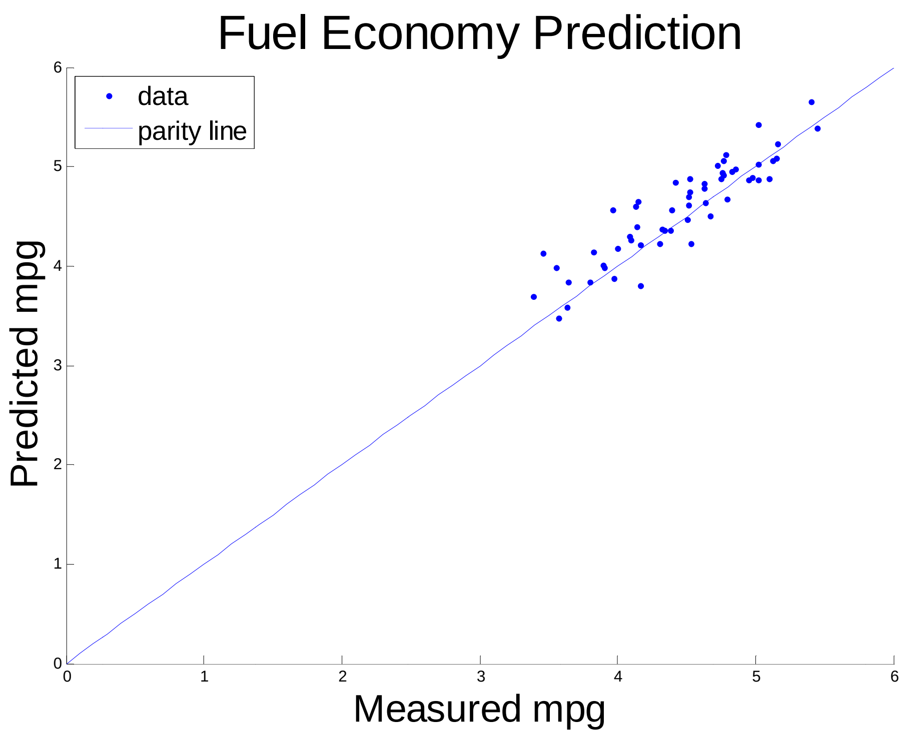
Weights				Metrics Used	Fuel Economy Average Error (%)	CO_2 Average Error (%)
Idle	Creep	Transient	Cruise			
-0.1519	0.0243	1.0488	0.0788	Velocity, Acceleration, Stops/mile	4.98	4.29
-0.1326		1.0552	0.0774	Velocity and Acceleration	4.59	4.36
	-0.1672	1.0995	0.0677	Velocity and Acceleration	4.83	4.89
		0.8433	0.1567	Velocity	5.02	4.36
	-0.2944	1.2944		Velocity	4.97	8.67



$$CO2^{UDDS} = -0.1326CO2^{idle} + 1.0552CO2^{trans} + 0.0774CO2^{cruise}$$

Baseline Cycles Used	Metrics Used	Average % Error	Average Error (g/s)	Max. Error (g/s)	R^2
Idle, Transient and Cruise	Velocity and Acceleration	4.36	0.52	2.02	0.82

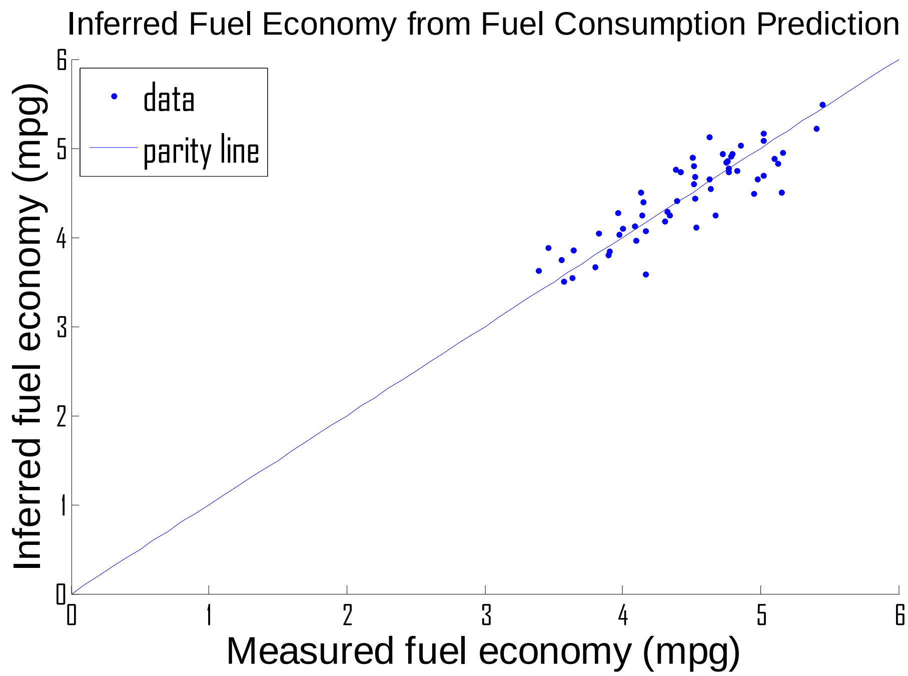
Figure 6. Results for CO_2 prediction for 56 trucks using recommended baseline cycles and metrics.



$$MPG^{UDDS} = -0.1326MPG^{idle} + 1.0552MPG^{trans} + 0.0774MPG^{cruise}$$

Baseline Cycles Used	Metrics Used	Average % Error	Average Error (mpg)	Max. Error (mpg)	R^2
Idle, Transient and Cruise	Velocity and Acceleration	4.59	0.20	0.67	0.82

Figure 7. Results for mpg prediction for 56 trucks using recommended baseline cycles and metrics.



Baseline Cycles Used	Metrics Used	Average % Error	Average Error (mpg)	Max. Error (mpg)	R^2
Idle, Transient and Cruise	Velocity and Acceleration	4.40	0.19	0.68	0.76

Figure 8. Inferred fuel economy based on fuel consumption prediction. Predicted CO_2 mass rate was converted to fuel economy in mpg using equations 15 and 16 (See *Predicted properties* section).

6.6 Extrapolation

Other predictions performed using the recommended combination of Idle, Transient and Cruise as baseline cycles and average velocity and average acceleration as metrics were tested with the High Speed Cruise cycle of the HDDT schedule as the "unseen" cycle. This prediction showed that the method did not extrapolate well (above 30% error), tending to overpredict fuel economy. Care must be taken when predicting cycles with average speeds higher than the maximum average speed of the baseline cycles.

Prediction of the Cruise cycle using Idle, Creep, and UDDS cycles, along with velocity and acceleration as metrics, resulted in high errors (38% error). Once more, the method did not extrapolate well.

The inaccuracy in the prediction using extrapolation could only be circumvented when the functional form assumed by the method (in this case a plane) accurately represented the nature of the function being extrapolated. The nature of the aerodynamic drag term in the road load equation (cubic velocity dependence) could affect the results when using baseline cycles without significant aerodynamic drag contribution (perhaps at speeds below 40 mph or so). Also, the High Speed Cruise cycle involved steadier engine operation than the Transient or Cruise cycles, a fact discussed in detail in recent papers [15,16,17]. A recommendation is to always include a relatively high speed cycle in the baseline cycles with the caveat that high speed is a relative term and engineering judgment plays an important role in the linear model development.

6.7 UDDS-Transient Interchange

The suggested similarity between the UDDS cycle and Transient cycle was investigated by interchanging these cycles in the analysis (using the UDDS as a baseline cycle along with the Idle and Cruise cycles with velocity and acceleration metrics). The prediction worked well with a 4.8% average error. The following equations show the values of the baseline cycles used in both cases.

Predicting UDDS cycle with Idle, Transient, and Cruise as baseline cycles:

$$w^{idle} = -0.1326$$

$$w^{trans} = 1.0552$$

$$w^{cruise} = 0.0774$$

Predicting transient cycle with Idle, UDDS, and Cruise cycles

$$w^{idle} = 0.1257$$

$$w^{UDDS} = 0.9476$$

$$w^{cruise} = -0.0733$$

As expected, the weight coefficient for UDDS was also nearly one. Note also that the sign of idle and cruise were interchanged meaning that UDDS has less Idle contribution than the Transient cycle and the Transient cycle has less Cruise cycle contribution than the UDDS cycle.

6.8 Recommendations (Truck Data)

Based on the results, the recommendation is to use average velocity and average acceleration as metrics. If another metric (and baseline cycle) is going to be added to the model, it is recommended to use stops per unit distance as the additional metric.

It is necessary to have baseline cycles which are sufficiently dissimilar so that they provide a wide basis for establishing the metric-dependent behavior. The best combination in terms of accuracy and economy is the use of Idle, Transient, and Cruise cycle in this work. Based on actual truck operation as found in the field, it is believed that these three cycles, or cycles with similar characteristics, would provide sufficient data to predict other cycles (or actual vehicle activity). However, it is recognized that there are always exceptions and engineering judgment will need to be used to determine the most appropriate baseline cycles that should be used. This combination of cycles has a good diversity of characteristics in terms of the metrics used, it has a zero velocity, zero acceleration cycle (Idle), a low velocity, high acceleration cycle (Transient), and a high velocity low acceleration cycle (Cruise). Cycles should cover a broad range of operation in order to be suitable as baseline cycles.

Due to the fact that the Idle cycle fuel economy (mpg) was zero and some information was lost during the modeling, it is recommended that the prediction be made in terms of CO_2 mass rate (g/s) and then convert to fuel economy (mpg). Extrapolation should be used with care.

7. Bus Data

The second vehicle type chosen was 40 foot transit buses. Chassis dynamometer data from two conventional diesel buses, two compressed natural gas buses, and one hybrid bus were used in this part of the research. The U.S. Department of Energy (DOE) and the U.S. Department of Transportation (DOT) sponsored the Center for Alternative Fuels, Engines, and Emissions (CAFEE) of West Virginia University (WVU) to conduct the program in cooperation with Washington Metropolitan Area Transit Authority (WMATA) [14]. Table 9 shows relative information of the buses.

Table 9. Transit buses analyzed in this research.

Bus Number	WMATA Bus No.	Technology	Manufacturer	Bus Type & Model Year	Engine Type & Model Year	GVW (kg)	Available Cycles
32	2640	CNG	John Deere	Orion 2005	RG6081 280hp/206kW 2005	19,334	16
35	2503	CNG	Cummins	Orion 2005	Cummins CG 280hp/206kW 2005	19,334	16
37	6003	Hybrid	Allison	New Flyer 2005	Cummins ISL280 2005	18,416	16
39	9654	Diesel	DDC	Orion 1992	DDC S50 275hp/202kW 2003	17,896	17
41	6150	Diesel	Cummins	New Flyer 2006	Cummins ISM280 2006	18,416	17

7.1 Cycles Used

Seventeen different cycles were available for the diesel buses and sixteen cycles were available for the CNG and hybrid buses. Table 10 shows the available cycles and average measured properties of velocity, acceleration and stops/mile. The measured Idle cycle average velocity was not equal to zero because some tests presented wheel speed noise during measurement as described above for the motivation to define idle and stop at velocities under 0.5 mph. Target speed-time traces for these cycles are shown in Appendix C.

Table 10. Average measured properties over 5 buses for 17 cycles used.

#	Cycle Name	Cycle ID	Average Measured Properties (over 5 buses)		
			Velocity (mph)	Acceleration (mph/s)	Stops/mile
1	CARB Idle Cycle	Idle	0.06	0.00	0.00
2	New York Bus Cycle	NYBus	3.54	0.25	18.71
3	Paris Cycle	PARIS	6.68	0.32	12.40
4	Manhattan Cycle	Manhattan	6.86	0.37	9.76
5	Washington Metro Transit Authority Cycle	WMATA	8.43	0.30	6.26
6	New York Composite Cycle	NY-Comp	8.75	0.15	7.21
7	Orange County Transit Authority Cycle	OCTA	12.22	0.41	4.87
8	Central Business District Cycle	CBD	13.08	0.52	6.80
9	Braunschweig Cycle	BRAUN	13.88	0.45	4.19
10	City Suburban Heavy Vehicle Cycle	CSHVC	14.02	0.27	2.29
11	Beeline Cycle	Beeline	14.03	0.43	3.73
12	European Test Cycle Urban	ETCURBAN	14.11	0.28	1.92
13	CARB Transient Cycle	TRANS	15.33	0.28	1.69
14	Urban Dynamometer Driving Schedule	Test_D	18.71	0.20	2.04
15	King County Metro Cycle	KCM	23.35	0.41	1.85
16	Arterial Cycle	ART	25.58	0.55	1.47
17	Commuter Cycle	COMM	44.37	0.18	0.17

7.2 Metrics and Cases Used

Based on the results from the truck study, average velocity and average acceleration were selected to perform the analysis. For each bus, all possible combinations of three baseline cycles were used to predict CO_2 mass rate (g/s) over the remaining thirteen or fourteen cycles. That is a total of 3040 predictions were made including 560 combinations among 16 cycles for three buses and 680 combinations among 17 cycles for two buses.

7.3 Bus Data Results and Analysis

As anticipated, not all combinations of baseline cycles were suitable to perform a good prediction. Figure 9 shows a histogram of average percent error lower than 200%. Approximately 44% of the combinations produced errors less than 20%. Note that some combinations of cycles produced very high prediction errors. There were errors above the 200% upper scale value shown in the figure but were not plotted. The method is not suitable if the cycles are ill chosen. For example, using two very low speed cycles plus idle to predict high speed behavior is fraught with difficulty, and is exacerbated if a poor combination of metrics is chosen. Note that average percentage error in this case is among 13 or 14 predicted cycles for the same vehicle while in the previous data set (truck data) the average percent error was among 56 vehicles over the same cycle (UDDS). One should not attempt to compare the errors from the two data sets; these errors are comparable within the same data set only.

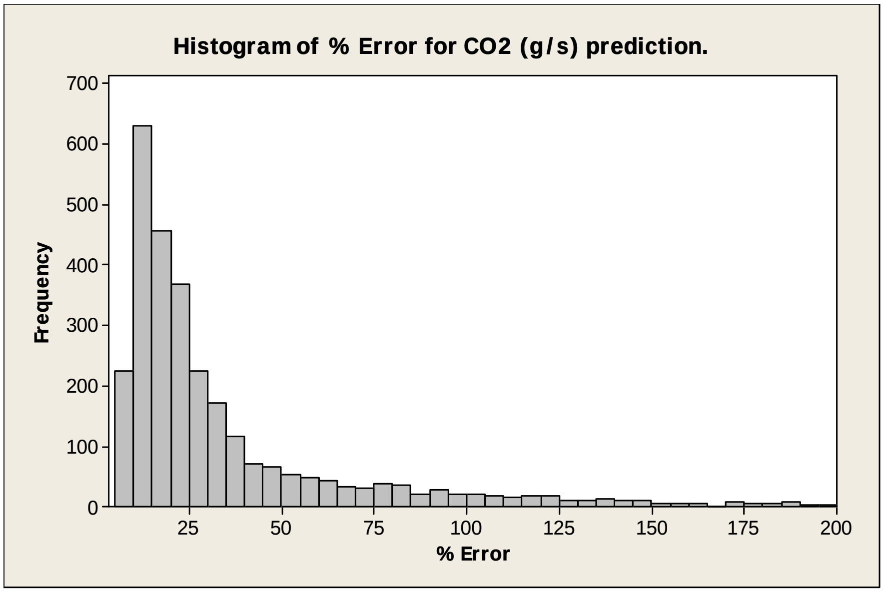


Figure 9. Histogram of average % Error among 13 or 14 predictions.

Tables 11 and 12 show the best predictions for each bus for CO_2 mass rate and fuel economy, respectively. Note that the Idle cycle is present in the best predictions for all vehicles. Figures 10 to 19 show parity plots of measured versus predicted values of CO_2 mass rate and fuel economy for the best predictions for buses 32, 35, 37, 39, and 41. By visual inspection of the slope of the linear regression line and R^2 correlation coefficients values it can be seen that CO_2 predictions were better than the fuel economy prediction. Moreover, CO_2 prediction errors were below 8.88% while fuel economy prediction errors were 15.89% or worst. The best baseline cycle combination for CO_2 was usually not the best baseline cycle combination for fuel economy, but the Idle cycle was present in both the best CO_2 mass rate and best fuel economy models. Most of the combinations included a cycle with relatively high average velocity such as COMM, ART, KCM, or Test_D and a transient cycle with relatively low average velocity such as WMATA, Paris, or OCTA. The KCM cycle appears to be valuable because it worked relatively well both as a low speed cycle or as a high speed cycle depending on the baseline cycle combination. The KCM cycle average velocity was approximately 50% of the highest average velocity of the cycles used (COMM cycle has an average velocity of 44.37mph) and the KCM cycle average acceleration was approximately 75% of the highest average acceleration (ART cycle with 0.55mph/s). Overall, values of average velocity above 18.7 mph produced average percentage errors below 10% when used as high speed, low acceleration baseline cycle and values of acceleration above 0.3 mph/s produced average percentage errors below 10% when used as low speed, high acceleration baseline cycles. Based on the results shown in Figure 14, hybrid vehicles appear to be able to be modeled using the linear modeling methodology presented here. However, additional hybrid vehicles and hybrid vehicle architecture will need to be investigated to substantiate this claim.

7.4 Extrapolation

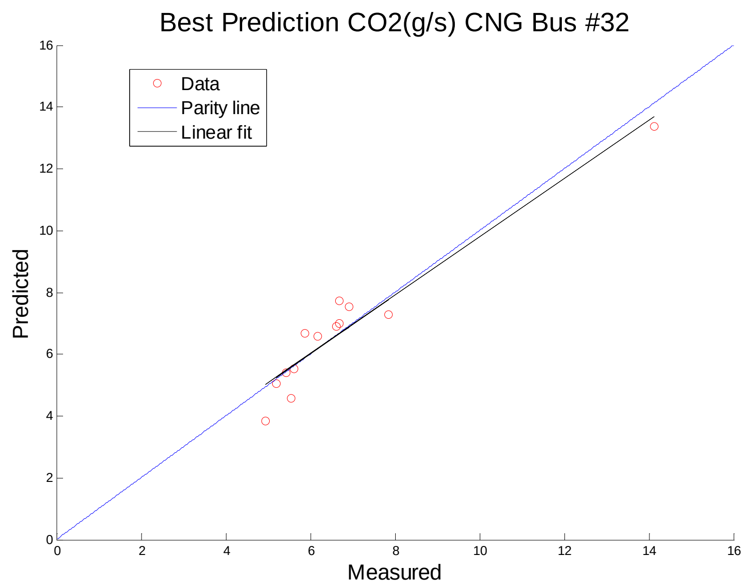
For diesel transit buses (Figure 16 and Figure 18) fuel consumption was under predicted for the COMM cycle due to extrapolation (predicting a cycle with higher average velocity than the baseline cycle with highest average velocity) and this brought the linear regression line down for the CO_2 mass rate plot causing the slope in the regression line to be less than one. However, it appears that as long as a high speed cycle was used as a baseline cycle, the extrapolation would not produce significant deviations between the measured and estimated values. CNG bus 35 (Figure 12) illustrated an exception to this observation. The best results for bus 35 were obtained when using baseline cycles idle, Paris and WMATA. The highest average velocity baseline cycle in this case was 8.43 mph for the WMATA cycle and was able to predict the COMM cycle with an average velocity of 44.37 mph within 1.12g/s. In this case higher average speed extrapolation is possible.

Table 11. Best CO_2 mass rate results for each bus.

Bus ID	Cycle Name			CO_2 (g/s)				
	Cycle A	Cycle B	Cycle C	% Error	Average Error (g/s)	Max. Error (g/s)	Std. Dev. Error (g/s)	R^2
32	Idle	Beeline	KCM	8.48	0.54	1.12	0.37	0.92
35	Idle	PARIS	WMATA	7.53	0.53	1.20	0.37	0.95
37	Idle	OCTA	KCM	8.17	0.51	1.29	0.40	0.98
39	Idle	KCM	ART	8.70	0.83	2.45	0.68	0.93
41	Idle	PARIS	KCM	8.88	0.76	2.33	0.65	0.93

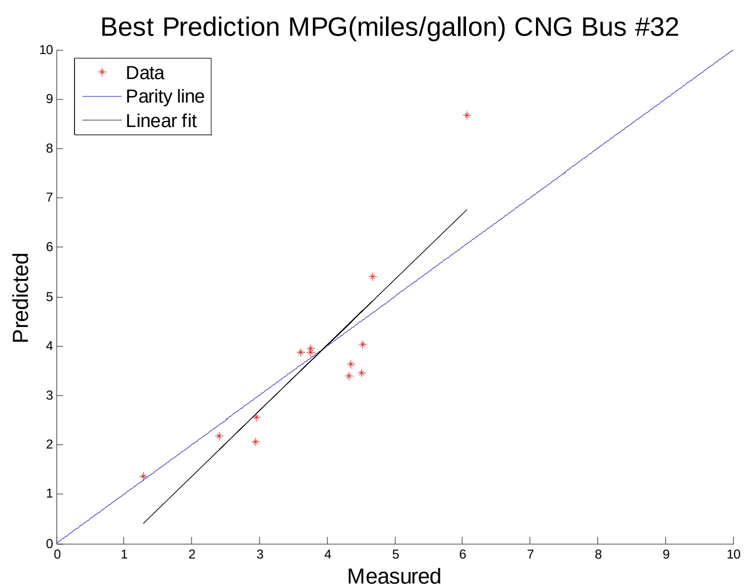
Table 12. Best fuel economy (mpg) results for each bus.

Bus ID	Cycle Name			Fuel Economy (mpg)				
	Cycle A	Cycle B	Cycle C	% Error	Average Error (mpg)	Max. Error (mpg)	Std. Dev. Error (mpg)	R^2
32	Idle	Manhattan	OCTA	15.89	0.67	2.61	0.67	0.77
35	Idle	BRAUN	KCM	19.73	0.70	1.57	0.58	0.60
37	Idle	OCTA	COMM	22.26	1.19	2.43	0.93	0.18
39	Idle	Manhattan	KCM	20.34	0.85	2.12	0.76	0.38
41	Idle	Manhattan	KCM	22.17	1.01	2.19	0.77	0.39



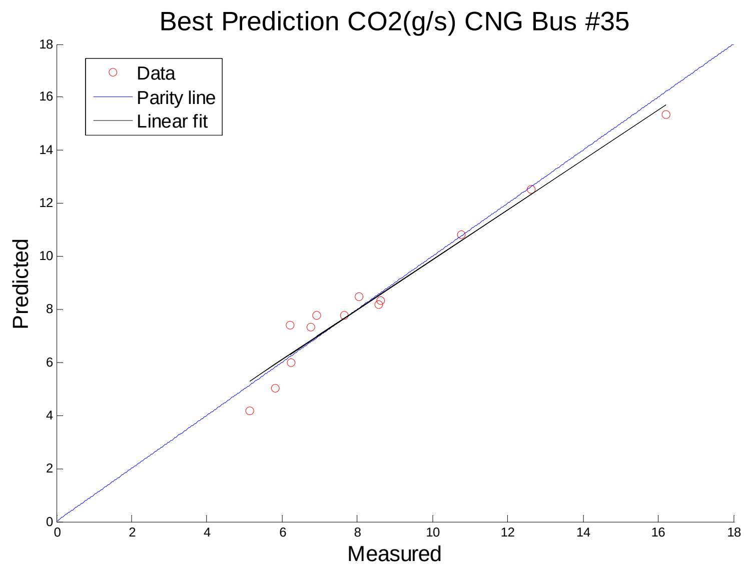
Bus ID	Cycle Name			CO_2 (g/s)				
	Cycle A	Cycle B	Cycle C	% Error	Average Error (g/s)	Max. Error (g/s)	Std. Dev. Error (g/s)	R^2
32	Idle	Beeline	KCM	8.48	0.54	1.12	0.37	0.92

Figure 10. Best CO_2 mass rate prediction, Bus #32.



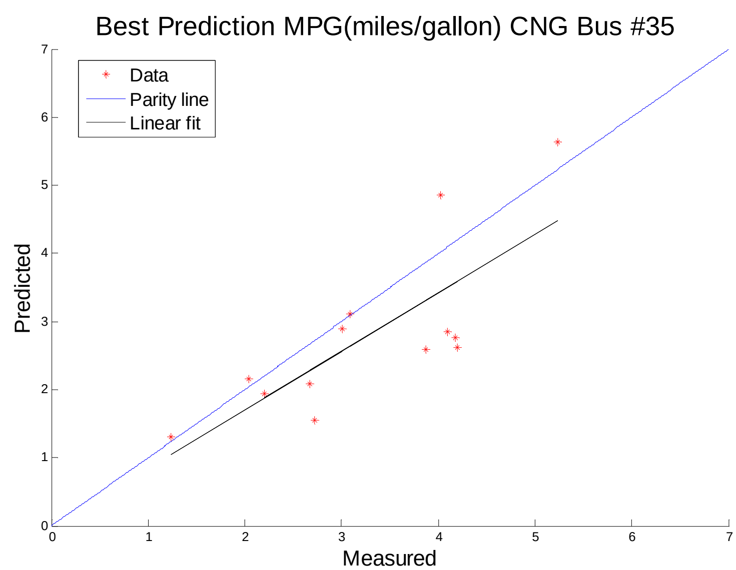
Bus ID	Cycle Name			Fuel Economy (mpg)				
	Cycle A	Cycle B	Cycle C	% Error	Average Error (mpg)	Max. Error (mpg)	Std. Dev. Error (mpg)	R^2
32	Idle	Manhattan	OCTA	15.89	0.67	2.61	0.67	0.77

Figure 11. Best fuel economy prediction, Bus #32



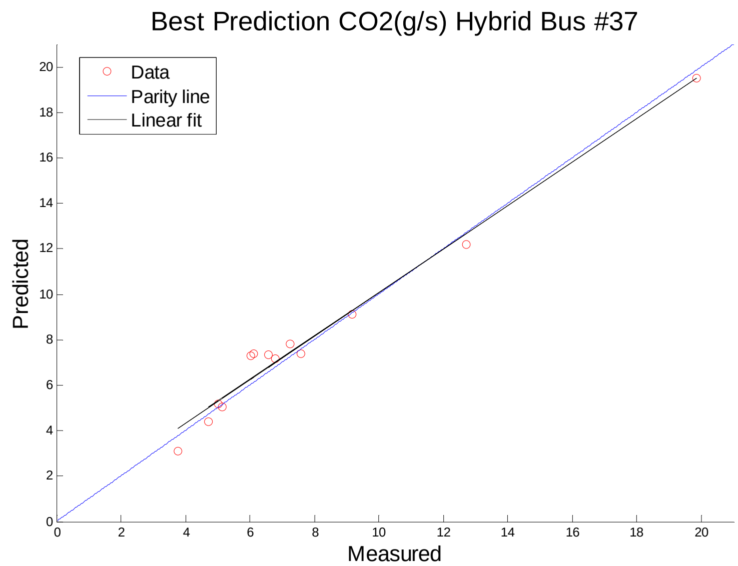
Bus ID	Cycle Name			CO_2 (g/s)				
	Cycle A	Cycle B	Cycle C	% Error	Average Error (g/s)	Max. Error (g/s)	Std. Dev. Error (g/s)	R^2
35	Idle	PARIS	WMATA	7.53	0.53	1.20	0.37	0.95

Figure 12. Best CO2 mass rate prediction, Bus #35.



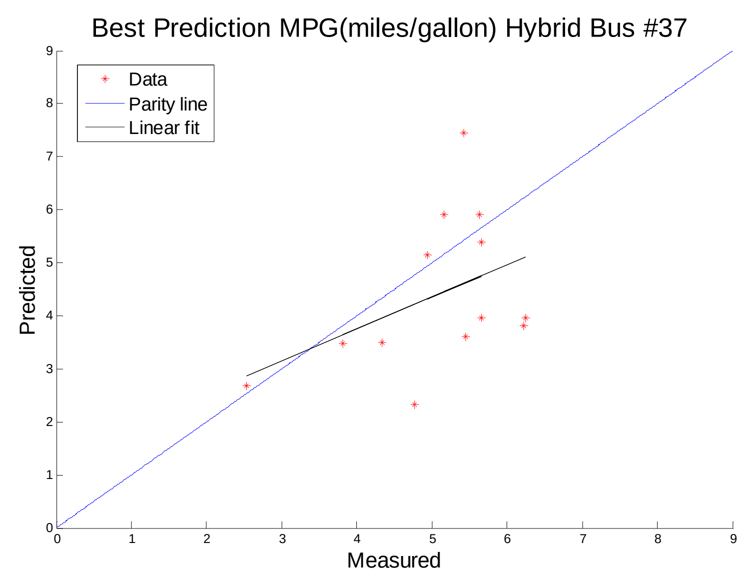
Bus ID	Cycle Name			Fuel Economy (mpg)				
	Cycle A	Cycle B	Cycle C	% Error	Average Error (mpg)	Max. Error (mpg)	Std. Dev. Error (mpg)	R^2
35	Idle	BRAUN	KCM	19.73	0.70	1.57	0.58	0.60

Figure 13. Best fuel economy prediction, Bus #35.



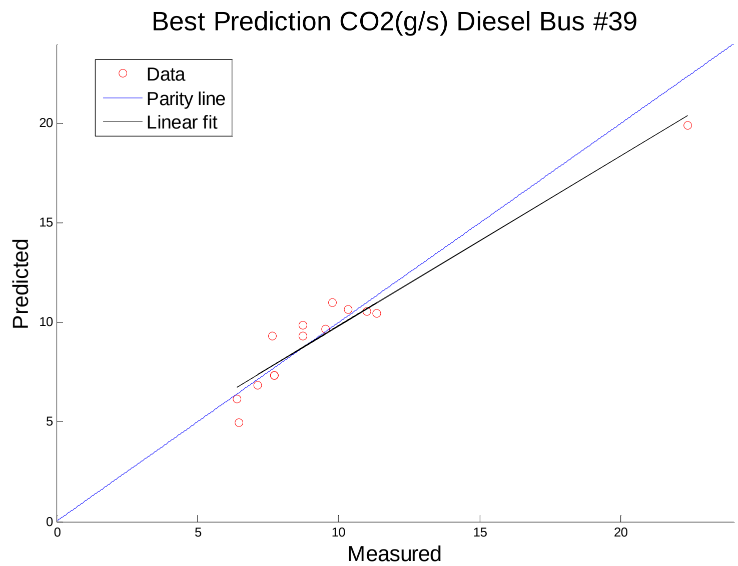
Bus ID	Cycle Name			CO2 (g/s)				
	Cycle A	Cycle B	Cycle C	% Error	Average Error (g/s)	Max. Error (g/s)	Std. Dev. Error (g/s)	R^2
37	Idle	OCTA	KCM	8.17	0.51	1.29	0.40	0.98

Figure 14. Best CO2 mass rate prediction, Bus #37.



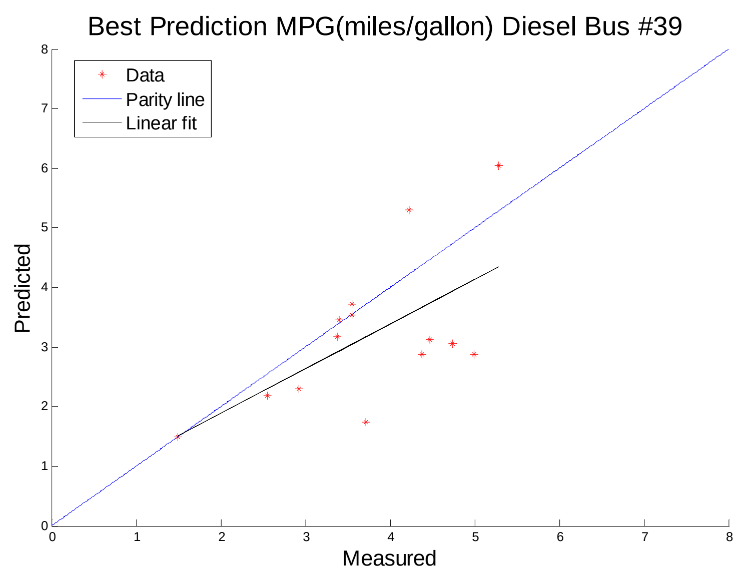
Bus ID	Cycle Name			Fuel Economy (mpg)				
	Cycle A	Cycle B	Cycle C	% Error	Average Error (mpg)	Max. Error (mpg)	Std. Dev. Error (mpg)	R^2
37	Idle	OCTA	COMM	22.26	1.19	2.43	0.93	0.18

Figure 15. Best fuel economy prediction, Bus #37.



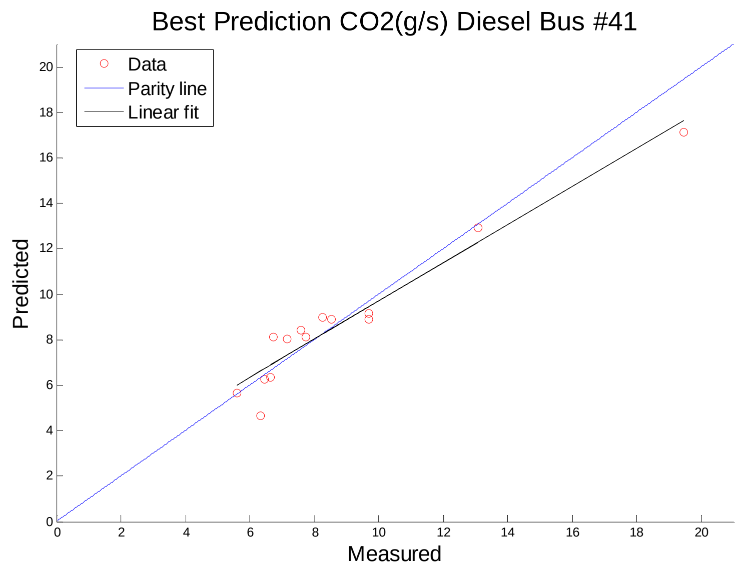
Bus ID	Cycle Name			CO_2 (g/s)				
	Cycle A	Cycle B	Cycle C	% Error	Average Error (g/s)	Max. Error (g/s)	Std. Dev. Error (g/s)	R^2
39	Idle	KCM	ART	8.70	0.83	2.45	0.68	0.93

Figure 16. Best CO2 mass rate prediction, Bus #39.



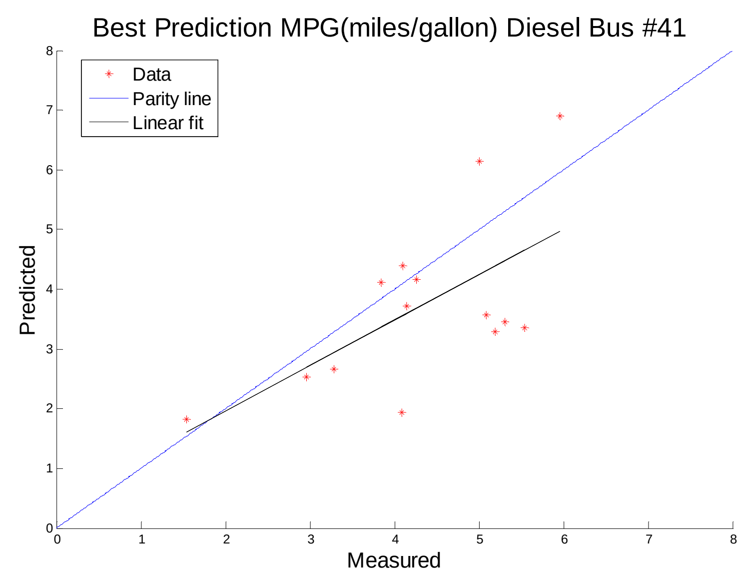
Bus ID	Cycle Name			Fuel Economy (mpg)				
	Cycle A	Cycle B	Cycle C	% Error	Average Error (mpg)	Max. Error (mpg)	Std. Dev. Error (mpg)	R^2
39	Idle	Manhattan	KCM	20.34	0.85	2.12	0.76	0.38

Figure 17. Best fuel economy prediction, Bus #39.



Bus ID	Cycle Name			CO2 (g/s)				
	Cycle A	Cycle B	Cycle C	% Error	Average Error (g/s)	Max. Error (g/s)	Std. Dev. Error (g/s)	R^2
41	Idle	PARIS	KCM	8.88	0.76	2.33	0.65	0.93

Figure 18. Best CO_2 mass rate prediction, Bus #41.



Bus ID	Cycle Name			Fuel Economy (mpg)				
	Cycle A	Cycle B	Cycle C	% Error	Average Error (mpg)	Max. Error (mpg)	Std. Dev. Error (mpg)	R^2
41	Idle	Manhattan	KCM	22.17	1.01	2.19	0.77	0.39

Figure 19. Best fuel economy prediction, Bus #41.

7.5 Comparison between CO_2 and Fuel Economy Predictions

The prediction of CO_2 mass rate tends to be a better method of prediction than a direct fuel economy prediction. This stems from the fuel economy at idle being equal for all vehicles (a value of zero by definition), whereas CO_2 mass rate for the Idle cycle was different (and non zero) for each vehicle. Using CO_2 mass rate provides additional information in the model. Another possible explanation is the more linear dependence between CO_2 and speed than fuel economy and speed as is shown by comparison of R^2 correlation coefficients of linear fits in Figure 20. The non-linearity of fuel consumption or of distance-specific emissions levels with respect to average speed is well-documented in “speed correction factors” which are often used in emissions inventory models, such as EMFAC.

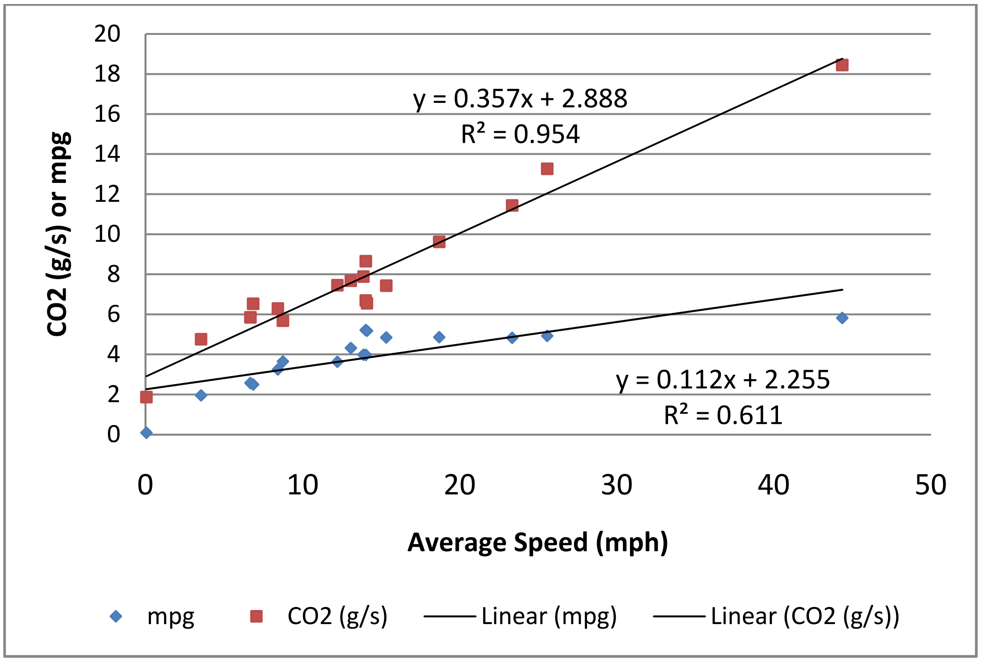


Figure 20. CO_2 mass rate and fuel economy as functions of average speed.

7.6 Best Bus Baseline Cycles

The key to obtaining a prediction with low error is the selection of suitable combinations of baseline cycles. A given baseline cycle is not “good” or “bad” by itself. Rather, it is the combination of individual baseline cycles that makes the predictive approach suitable or not. Also, a baseline cycle can have low errors with some metrics but have high errors with other metrics. Further, the success of the approach may vary according to the application because in some cases the best average prediction for a fleet of vehicles may be the objective, whereas in other applications there may be a need to constrain the worst individual error in the prediction. To this end, an analysis was performed to identify which cycles are more associated with predictions with low errors using average velocity and average acceleration. Figure 21 shows a histogram of the frequency of a given cycle in the combinations with percentage error less than 10%. The analysis was done using the CO_2 mass rate data. The plots show that the Idle cycle should be used in every prediction. Note also that cycles like ETCURBAN or NYBus are not present in any combination with error less than 10%. These two cycles are transient, low speed but their values of acceleration are below 0.3 mph/s.

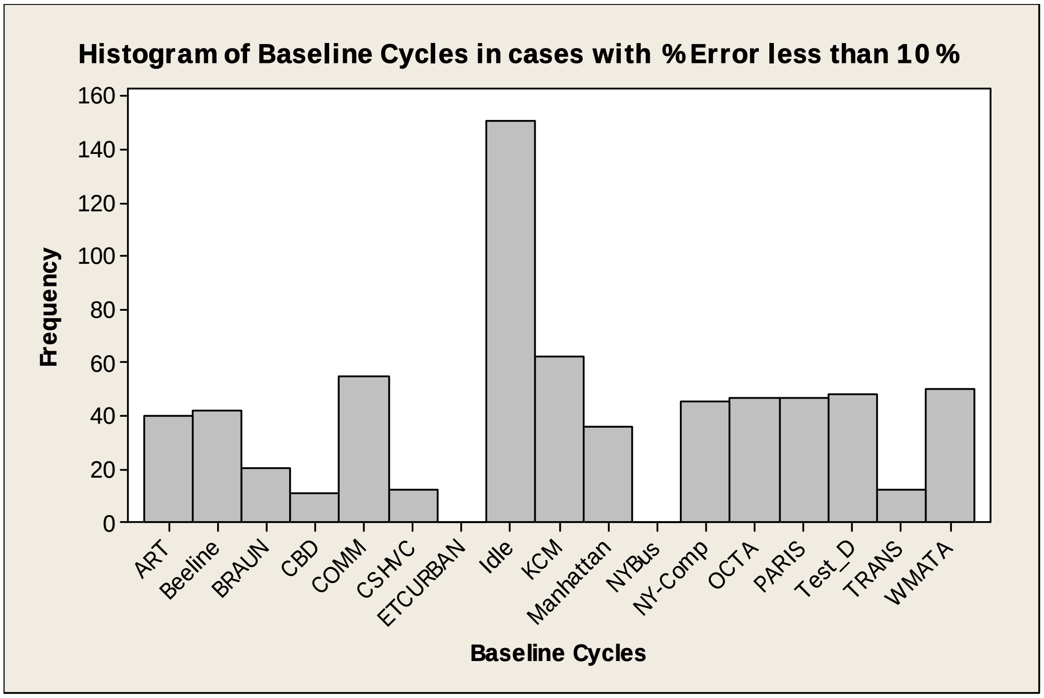


Figure 21. Frequency of a baseline cycle in prediction with average error below 10%.

7.7 Best Bus Baseline Combinations

Table 13 shows the three combinations of baseline cycles with the lowest error for the prediction of CO_2 mass rate for the five buses considered. The combination of Idle cycle, a relatively low average speed with high average acceleration cycle, and a relatively high speed cycle was present in the three combinations. Note that these combinations produced prediction results with less than 10% average error for all buses over a very wide range of cycles.

Table 13. Best bus baseline combinations results for CO2 (g/s) prediction.

Baseline Cycles Used	Average Percentage Error (%)					Average Percent. Error (%) (5 buses)	Max. Absolute Error (g/s)
	CNG #32	CNG #35	Hybrid #37	Diesel #39	Diesel #41		
Idle OCTA KCM	8.61	7.78	8.17	8.75	9.26	8.51	3.95
Idle PARIS KCM	9.11	7.55	8.89	8.72	8.88	8.63	3.18
Idle OCTA COMM	8.52	7.80	8.38	9.21	9.80	8.74	2.20

7.8 Other Possible Bus Baseline Cycle Combinations

Other baseline combinations identified in the bus data with average percentage error below 10% among five buses are summarized in Table 14. All combinations include Idle cycle, and most of them included one intermediate transient cycle and one relatively high speed cycle. Baseline cycles should cover a broad range of operation encompassing the unseen cycle.

Table 14. Combinations of baseline cycles with average percentage error below 10%.

Cycles	Average Percentage Error (over predicted cycles)					Average Percentage Error
	Bus 32	Bus 35	Bus 37	Bus 39	Bus 41	
Idle KCM OCTA	8.61	7.78	8.17	8.75	9.26	8.51
Idle KCM PARIS	9.11	7.55	8.89	8.72	8.88	8.63
Idle KCM Manhattan	8.51	8.08	NA	8.84	9.14	8.64
Idle Manhattan ART	NA	8.10	NA	8.86	9.21	8.72
Idle OCTA COMM	8.52	7.80	8.38	9.21	9.80	8.74
Idle PARIS ART	NA	7.54	9.95	8.76	9.05	8.82
Idle WMATA KCM	9.00	7.56	8.20	9.73	10.42	8.98
Idle OCTA Test_D	10.16	8.41	8.24	9.56	9.54	9.18
Idle ART COMM	NA	7.79	9.89	9.61	9.80	9.27
Idle WMATA COMM	9.02	7.74	8.67	10.68	12.06	9.63
Idle WMATA Test_D	10.18	8.13	8.38	10.35	11.13	9.63
Idle WMATA ART	NA	7.53	10.45	10.17	10.45	9.65
Idle KCM COMM	8.48	8.57	8.43	11.14	11.67	9.66
Idle BRAUN COMM	9.41	8.74	11.17	9.34	9.75	9.68
Idle PARIS Test_D	10.94	8.15	9.55	10.07	9.84	9.71
Idle OCTA ART	NA	7.80	11.52	8.76	10.76	9.71
Idle Beeline KCM	8.48	9.15	8.38	9.66	13.38	9.81
Idle Test_D ART	NA	9.03	10.28	10.59	9.45	9.84
Idle PARIS COMM	9.75	7.85	10.47	10.44	10.93	9.89
Idle Beeline COMM	8.58	8.52	8.77	9.97	13.71	9.91
Idle OCTA TRANS	8.94	10.55	8.72	11.28	10.37	9.97
Idle Manhattan CSHVC	9.66	9.53	NA	9.74	11.00	9.98
Idle Beeline Test_D	9.95	8.56	8.52	9.81	13.13	9.99

NA – Not Available.

7.9 Non Compatible Bus Cycle Combinations

A non compatible pair is defined as a pair of cycles that produce prediction average percentage errors above 50% when used as baseline cycles. Some non compatible cycle pairs were identified. Beeline cycle was not compatible with Braun, CBD, ETCURBAN or OCTA cycles. ETCURBAN was not compatible with CSHVC, COMM, KCM or ART cycles. It is clear that it is necessary to have cycles which are sufficiently dissimilar so that they provide an accurate basis for establishing the metric-dependent behavior. For example CSHVC and ETCURBAN resulted in very high average prediction errors of above 2000%. This is believed to be due to the similarity between their metrics (average velocities of 14.02mph and 14.11mph and average accelerations of 0.27mph/s and 0.28mph/s) so that the ability to extrapolate using the data is severely curtailed. Defining a plane based on three points when two points are in (or very near) the same location, results in an ill-defined surface. Although matrix inversion (solving of simultaneous equations) is possible in that scenario, the solution becomes sensitive to changes in one particular metric. It is speculated that experimental error then becomes a first order effect in the analysis.

7.10 Best Bus Data Combination: Idle, OCTA, and KCM

Table 15 shows the results for the combination of baseline cycles with the lowest error. Figure 22 further illustrates how this combination predicted each cycle to a high fidelity and could be useful to see when fuel consumption for one cycle is consistently overpredicted or underpredicted. For example it can be seen that CBD, CSHVC, ETCURBAN, and Transient cycles' fuel consumption were overpredicted for all of the buses. The COMM cycle fuel consumption was mostly underpredicted (particularly for the diesel buses) because extrapolation appeared to be unable to account for the aerodynamic drag portion of the road load equation. Figure 23 shows a parity plot of measured versus predicted values for all the predictions using the recommended combination. Note that extrapolation caused subtle underpredictions.

Table 15. Results for recommended combination of baseline cycles for the bus data.

Bus ID	Cycle Name			CO2 (g/s)				
	Cycle1	Cycle2	Cycle3	% Error	Average Error	Max. Error	Std. Dev. Error	R^2
35	Idle	OCTA	KCM	7.78	0.53	1.14	0.35	0.96
37	Idle	OCTA	KCM	8.17	0.51	1.29	0.40	0.98
32	Idle	OCTA	KCM	8.61	0.50	1.39	0.35	0.95
39	Idle	OCTA	KCM	8.75	0.81	2.11	0.61	0.95
41	Idle	OCTA	KCM	9.26	0.72	2.09	0.57	0.94

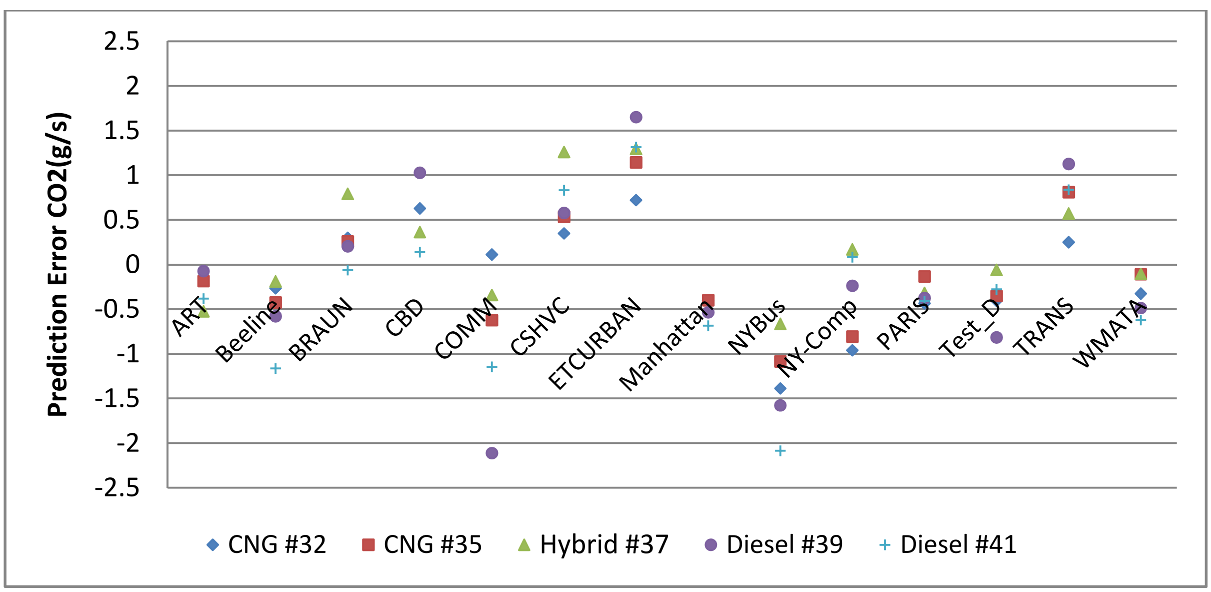


Figure 22. Prediction errors using idle, OCTA and KCM as baseline cycles and average velocity and average acceleration as metrics.

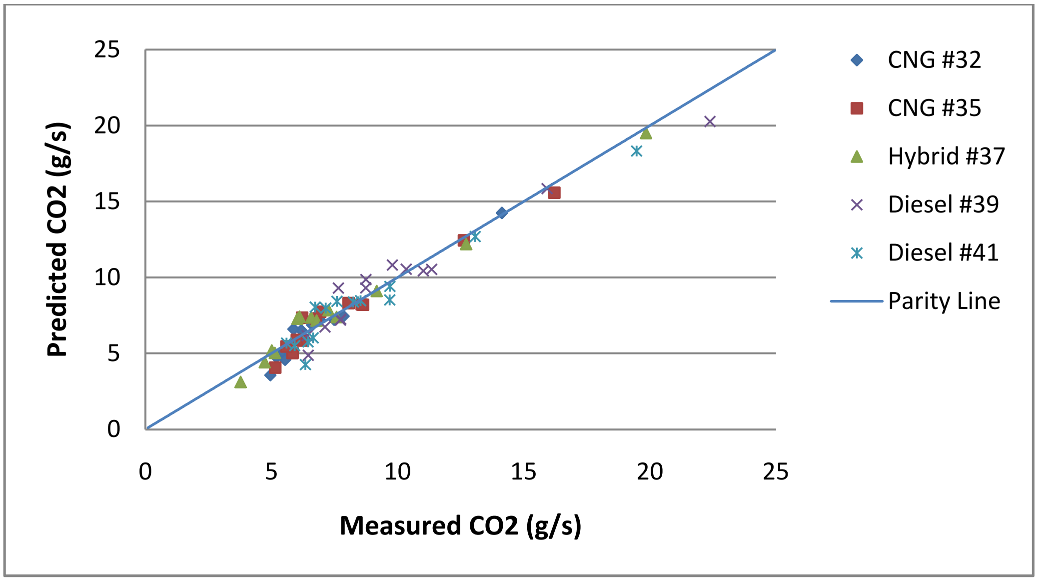


Figure 23. Parity plot for prediction using Idle, OCTA, and KCM cycles and velocity and acceleration metrics.

7.11 Alternative Metrics

An exploratory analysis was completed to discern if other metrics had the potential to replace acceleration or to be used in conjunction with velocity and acceleration to obtain improved results. Figure 24 shows the ratio of average percentage error for alternative metrics over average percentage error using velocity and acceleration. A value below one for this ratio meant that the alternative metrics combination had the potential to have lower errors than the velocity and acceleration combination alone. It can be seen that stops per mile and average of (velocity squared) are metrics that could reduce the error when compared to using just the velocity and acceleration metrics. The plot also shows that the accuracy of prediction could be improved by adding one more metric to the analysis but at the cost of adding one more baseline cycle. Only the best possible case (the case with minimum average percent error) was used for this analysis and further research should be done in order to validate these conclusions. The next section shows a more detailed analysis using stops per mile as an alternative metric.

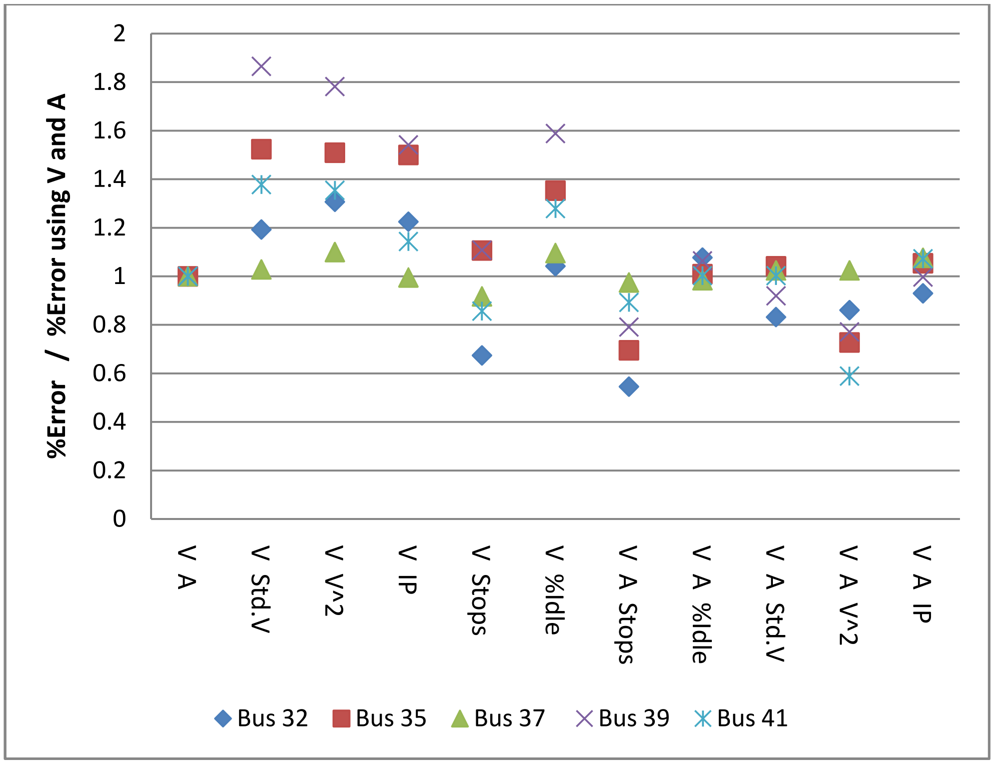


Figure 24. Percentage error ratios when using other metrics combinations.

7.12 Using Stops per Mile as a Metric

Based on the results shown in Figure 24, the bus data were modeled using the velocity and stops per mile metrics with different combinations of three baseline cycles. The results with the lowest errors are shown in Table 16. The data was evaluated using velocity, acceleration, and stops per mile using different combinations of four baseline cycles. Table 17 shows the results with the lowest errors for this case. It is worth mentioning that the idle cycle was still present in all of the cases.

Table 16. Best results with velocity and stops/mile.

Bus ID	Cycle A	Cycle B	Cycle C	% Error	Average Error (g/s)	Max. Abs. Error (g/s)	Std. Dev. Error (g/s)	R^2
32	Idle	NYBus	CBD	6.08	0.47	1.89	0.49	0.97
35	Idle	NYBus	KCM	8.99	0.77	2.55	0.63	0.94
37	Idle	NYBus	WMATA	6.56	0.46	1.23	0.41	0.98
39	Idle	PARIS	Test_D	9.55	0.94	1.85	0.45	0.95
41	Idle	NYBus	COMM	7.82	0.59	1.42	0.51	0.89

Table 17. Bus results with lowest error using velocity, acceleration, and stops per mile metrics.

Bus ID	Cycle A	Cycle B	Cycle C	Cycle D	% Error	Average Error (g/s)	Max. Abs. Error (g/s)	Std. Dev. Error (g/s)	R^2
32	Idle	NYBus	BRAUN	COMM	4.92	0.32	0.55	0.19	0.91
35	Idle	NYBus	WMATA	COMM	5.65	0.40	1.13	0.33	0.94
37	Idle	NYBus	PARIS	Test_D	6.97	0.48	1.23	0.42	0.98
39	Idle	NYBus	BRAUN	KCM	6.82	0.63	1.63	0.42	0.98
41	Idle	Manhattan	OCTA	Test_D	8.15	0.63	1.33	0.45	0.97

7.13 Best Combination: Idle, NYBus, and KCM

The Idle, NYBus, and KCM combination of baseline cycles resulted in the lowest error for the bus data when the stops per mile metric was used. Note that using velocity and acceleration as metrics, the best combination of baseline cycles was Idle, OCTA and KCM and when using velocity and stops per mile as metrics, the best combination of baseline cycles was Idle, NYBus, and KCM. The NYBus cycle was not a good baseline cycle when using average acceleration but was one of the best cycles when using stops per mile. Table 18, Figure 25, and Figure 26 show these result in more detail.

Table 18. Best results using Idle NYBUs and KCM. Average velocity and stops/mile.

Bus ID	Cycle Name			CO_2 mass rate (g/s)				
	Cycle A	Cycle B	Cycle C	% Error	Average Error (g/s)	Max. Abs. Error (g/s)	Std. Dev. Error (g/s)	R^2
32	Idle	NYBus	KCM	6.32	0.49	2.28	0.57	0.98
37	Idle	NYBus	KCM	6.78	0.45	1.31	0.45	0.98
41	Idle	NYBus	KCM	7.92	0.59	1.37	0.51	0.96
35	Idle	NYBus	KCM	8.99	0.77	2.55	0.63	0.94
39	Idle	NYBus	KCM	9.63	0.96	1.98	0.52	0.94

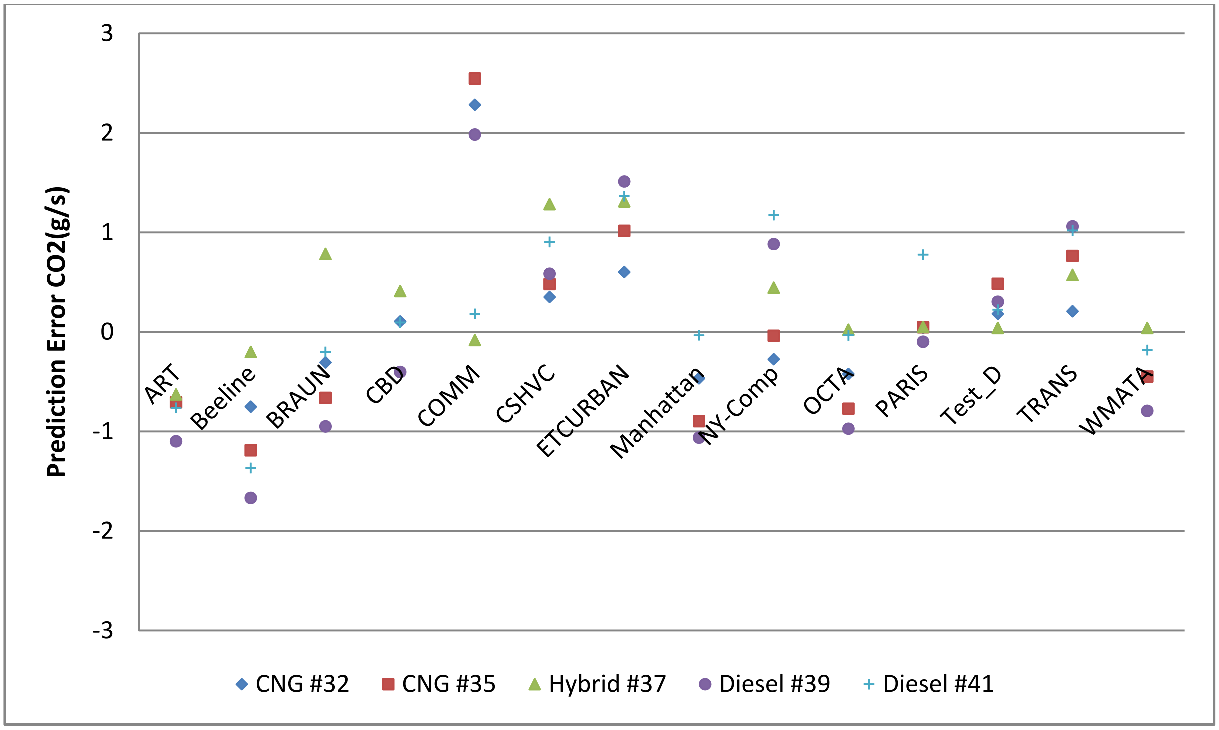


Figure 25. Prediction errors using Idle, NYBus, and KCM as baseline cycles and average velocity and stops per mile as metrics.

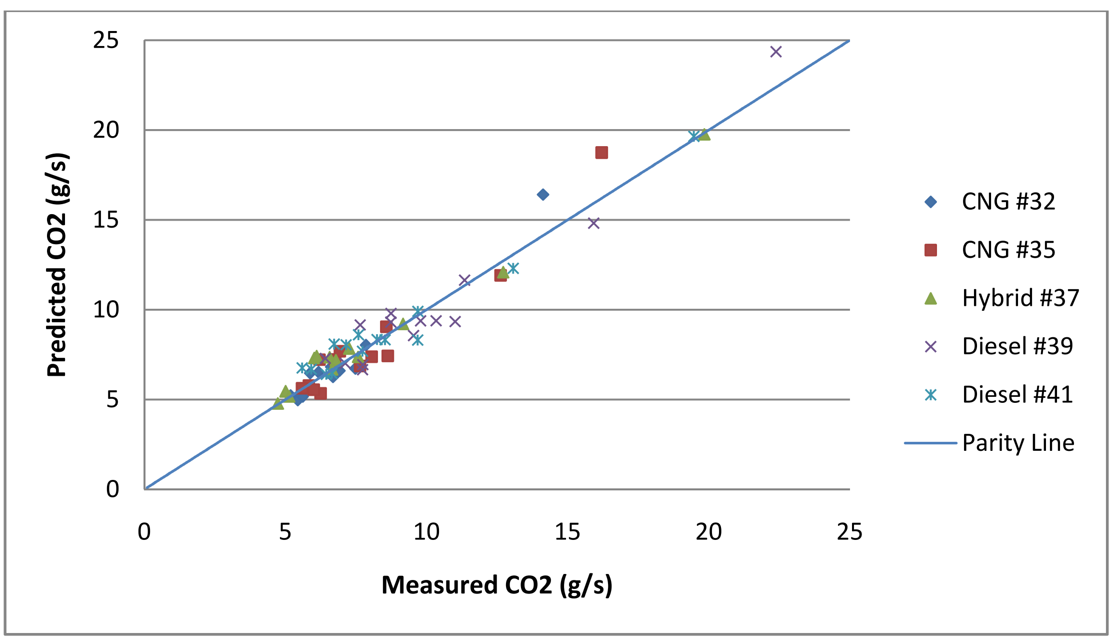


Figure 26. Parity plot for prediction using Idle, NYBus, and KCM using velocity and stops per mile metrics.

7.14 Bus Data Recommendations

Average velocity, average acceleration, and stops per mile were the metrics identified to predict CO_2 mass rate from unseen cycles. The Idle cycle must be present as a baseline cycle, along with a relatively slow transient cycle (about 25% of the maximum average speed and average acceleration higher than 0.3 mph/s) and a relatively high speed cycle, preferably with an average velocity at or above the average velocity of the unseen cycle. Care must be used when extrapolating higher average speed cycles relative to the cycles used in the prediction.

It is interesting to note that KCM cycle was identified as a suitable cycle using both average velocity and average acceleration as metrics and average velocity and stops per mile as metrics. It appears as though this cycle has advantageous characteristics that minimize the errors in the linear model.

8. Black Box Model (Neural Networks)

The second approach used to predict fuel consumption used the training of a neural network with continuous second-by-second data (instantaneous properties and instantaneous fuel consumption) from baseline cycles. The model was then used to predict second-by-second fuel consumption over an unseen cycle, and the cycle-averaged CO_2 emissions mass rate could be determined. Training the neural network requires some skill because one must select the training data appropriately. Neural networks require a large diversity of training in order to capture all of the details of the physical system. However one must avoid overtraining of the neural network.

Chassis dynamometer data for 56 heavy heavy-duty trucks operating at a nominal 56,000 lbs were used in this part of the research. This data were the same as used to perform the linear modeling for the truck data. This data were gathered as part of the Coordinating Research Council E-55/E59 program, which was created to characterize heavy-duty trucks emissions in California.

Training of the neural network was done with the second-by-second data from all of the transient cycles and cruise cycles that were available from a given vehicle. Input data included properties such as instantaneous velocity, instantaneous acceleration, instantaneous square of velocity, instantaneous cube of velocity, and instantaneous inertial power. The output variable was CO_2 mass rate emissions, in g/s. One neural network was created and trained for each of the 56 vehicles considered. The neural network then was used to predict second-by-second CO_2 mass rate emissions for the UDDS cycle (validation cycle).

Several network architectures were evaluated using the Matlab Neural Network Toolbox [5]. These architectures included different number of hidden nodes, number of hidden layers, and different types of transfer function of the nodes. Different combinations of metrics were also used. The best results were obtained using a back propagation neural network with two hidden layers, 100 neurons in the first layer with a tan-sigmoid transfer function and one linear neuron in the output layer. The input layer used instantaneous values of velocity, velocity cubed, and inertial power as metrics. Figure 27 shows a schematic of the neural network architecture. The scope present program did not include the optimization of the neural net architecture for the specific application.

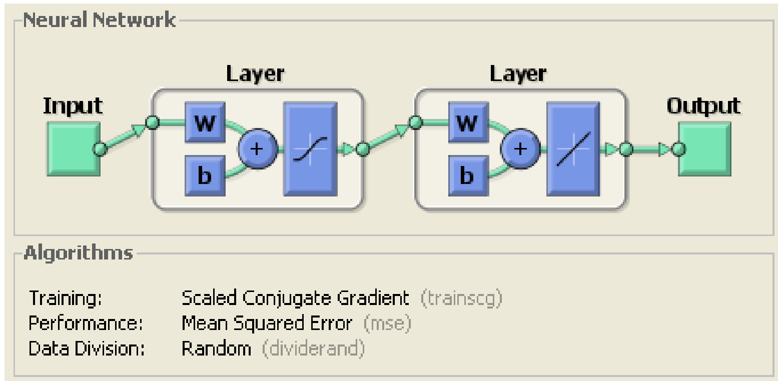


Figure 27. Schematic of neural network architecture.

8.1 Neural Network Results

Figure 28 shows a representative example of the results obtained for one particular vehicle. It appears that the neural net was able to capture the overall trend with an acceptable accuracy. However, between 500 seconds and 800 second of the UDDS cycle, the neural net underpredicted the measured response. Causes for second-by-second differences might be adscribed to the binary nature of cooling fan load, the use of a different gear than anticipated, or the use of an engine control strategy that not anticipated by the training data set. The overall results were calculated by integrating the instantaneous results and are summarized in Figure 29 where each data point represents one UDDS cycle (There are more than 56 data points because of repeated tests). The model was systematically underestimating the average fuel consumption of the UDDS cycle.

Neural network analysis has some disadvantages with respect to the linear model. The main one is that second-by-second data is required and that there are thousands of data points (at 1Hz) compared with only a few properties used in the linear model. Another disadvantage is that the prediction is not unique, because the neural network model depends on the selection of training parameters, the network architecture, and the algorithm used.

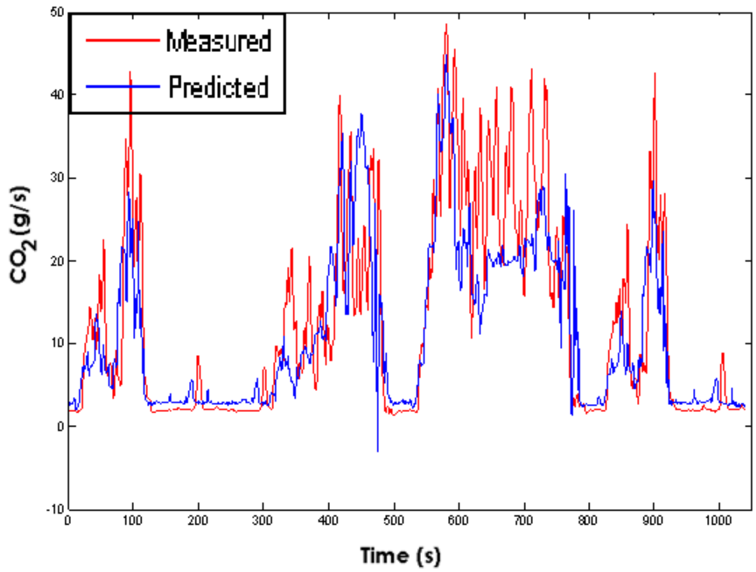


Figure 28. Neural network results in the prediction of UDDS cycle CO_2 mass rate emissions.

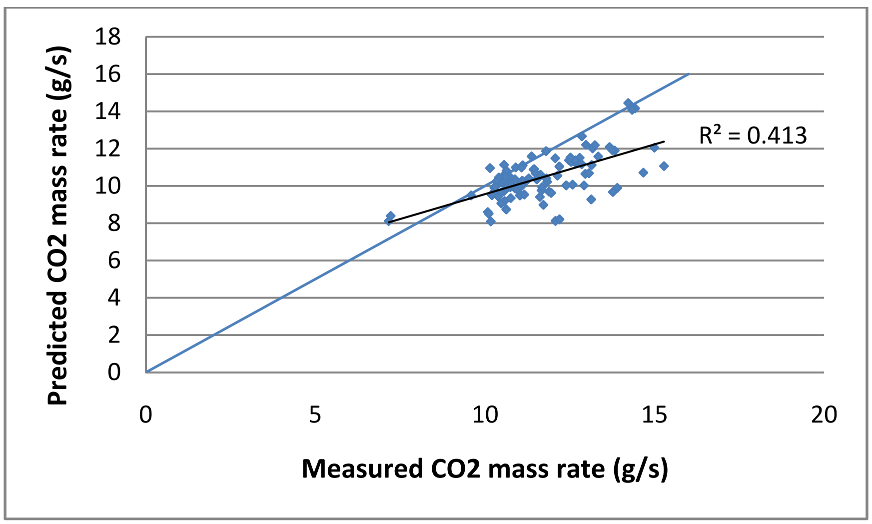


Figure 29. Summary of neural network prediction of CO_2 mass rate (g/s). Prediction error 10.24%.

9. PSAT Commercial Software Model

PSAT is a forward-looking model that simulates fuel economy and performance in a realistic manner taking into account transient behavior and control strategy [6]. PSAT is also called a command-based model [7]. The necessary wheel torque to reach the desired speed is estimated by passing information from the driver model to the vehicle controller (different components), such as throttle command for the engine, gear number for transmission, and mechanical braking for wheels [8]. There are three main components losses and they include the inertia of the vehicle, the aerodynamic drag, and the rolling resistance. These losses are added together to produce a rough estimate for the torque demand at the vehicle's wheels. Then decisions about how different components work are made based on the driver demand and the latest information from the components' sensors. Eventually, the vehicle controller commands (i.e., engine torque) are transformed and can then be used by the respective component models (i.e. throttle). Briefly, the forward-looking method works by modeling the command of the driver which in turn causes the appropriate components' response to meet the desired vehicle speed [7]. As components react to the commands as if a person were driving the vehicle, the user can implement advanced component models by taking into account transient effects (such as engine starting, clutch engagement/disengagement, or shifting) or developing realistic control strategies [7]. Figure 30 shows the PSAT graphical user interface.

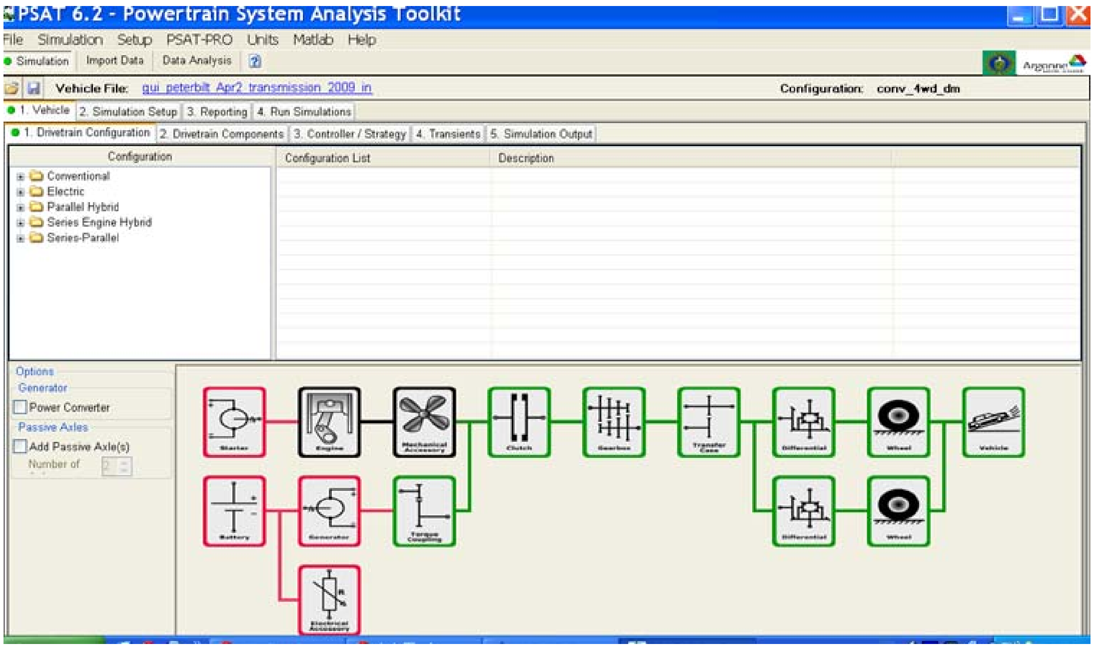


Figure 30. The PSAT graphical user interface.

A PSAT model was developed for a 1998 Peterbilt truck, with a 410hp C12 Caterpillar engine. CO_2 mass rate was predicted following the procedure below:

1) A PSAT model was developed (Figure 30)for the truck listed above.

2) The model was run over Idle and Transient cycles, and the results were compared to measured values in order to find the effective coefficient of rolling resistance.

3) Keeping the rolling resistance fixed, the model was evaluated over the Cruise cycle, and the results were compared to measured values in order to find the aerodynamic drag coefficient.

4) Steps 2 and 3 were repeated in order to find the best fit between measured and PSAT simulated results.

5) Finally, the model was evaluated over the UDDS cycle and CO_2 mass rate predictions were compared to measured values.

9.1 PSAT Results

Figures 31 and 32 show the parity plot of measured versus predicted values of CO_2 mass rate in (g/s) for Transient cycle and Cruise cycle, respectively. The coefficient of rolling resistance for this prediction was 0.0136, and the aerodynamic drag coefficient 0.37. These are best fit values, but the drag coefficient is low and the rolling resistance is high in comparison to common wisdom. Figure 33 shows the parity plot of measured versus predicted values of CO_2 mass rate in (g/s) for UDDS cycle. Second-by second prediction of the UDDS cycle is good with a percentage error below 4%. However, the procedure of selecting components and assembling the model should be repeated for each different vehicle that needs to be simulated.

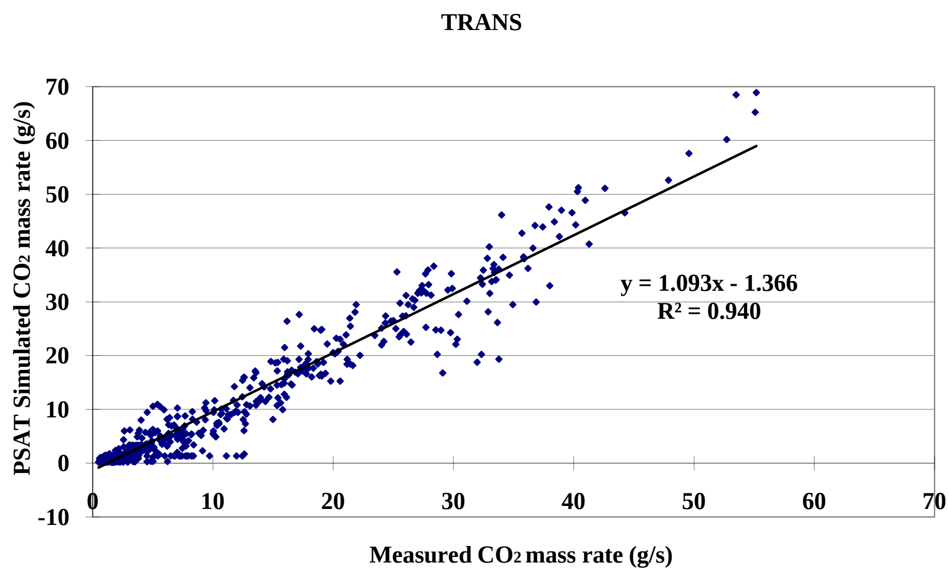


Figure 31. CO_2 mass rate prediction results for Transient cycle. Predicted mass rate: 9.30 g/s; Measured mass rate: 9.76 g/s; Prediction error 4.68%. Coefficient of rolling resistance 0.0136.

CRUISE

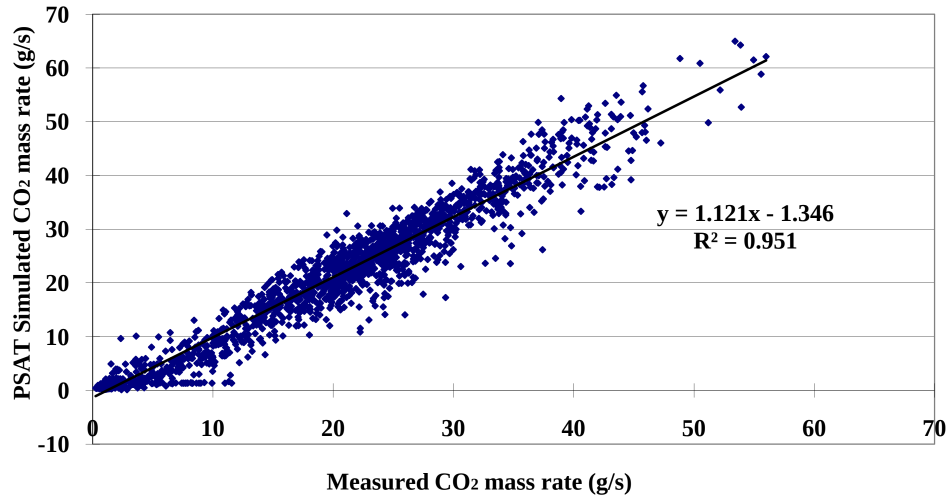


Figure 32. CO_2 mass rate prediction results for Cruise cycle. Predicted mass rate: 19.00g/s; Measured mass rate: 18.14g/s; Prediction error 4.69%. Aerodynamic drag coefficient 0.37.

UDDS

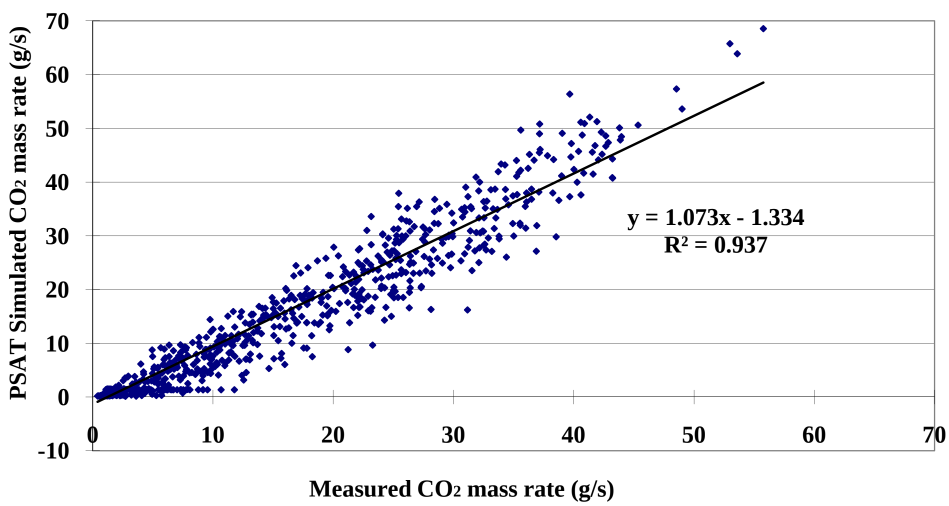


Figure 33. CO_2 mass rate prediction results for UDDS cycle. Predicted mass rate: 11.68 g/s; Measured mass rate: 12.13 g/s; Prediction error 3.69%.

10. Conclusion

A linear model methodology for the prediction of heavy-duty vehicle fuel economy based on measured chassis dynamometer test cycles and properties of those cycles was developed and verified. The methodology allowed for the prediction of fuel economy from vehicles operating on a number of different chassis dynamometer cycles based on relatively few experimental measurements. The results of the application of the linear model to a set of fifty-six heavy heavy-duty trucks operating over five different cycles showed that the use of average velocity and average positive acceleration as metrics produced the best results in terms of average percentage error (less than 5%). The results of the application of the linear model to a set of five buses operating over up to seventeen different cycles showed again that average velocity and average positive acceleration were suitable metrics to predict fuel economy with reasonable accuracy (less than 10% average percentage error). If another metric (and baseline cycle) is going to be added to the model, it is recommended to use stops per unit distance as the additional metric. It was also found that baseline cycles must include Idle cycle, along with a relatively slow transient cycle and a relatively high speed cycle, preferably with an average velocity at or above the average velocity of the unseen cycle. Based on the results obtained with both data sets, it was recommended that the prediction be made in terms of CO2 mass rate (g/s) and then convert to fuel economy (mpg).

Two alternative approaches using neural networks and the commercial simulation software PSAT were also developed and verified. The results of the application of these modeling strategies produced average percentage errors of the order of 10% and 4% respectively. The main disadvantages of these alternative approaches with respect to the linear model were their inherent complexity (application difficulty) and the need to use continuous (second-by-second) data.

11. References

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Appendix A– Weight Correction

Two types of weight correction techniques were applied to a subset of the truck data. Table 19 shows information of the eleven trucks used. Test data for three different weights (30,000lbs, 56,000lbs, and 66,000lbs) over Idle, Creep, Transient, and Cruise cycles were available for these trucks.

The first weight correction technique consisted of calculating the "percent change in CO_2 emissions per percent change in test weight." Figure 33 shows a plot of CO_2 mass rate percentage change as a function of percentage change in weight for the Creep, Transient, and Cruise cycles. Each point represents the average change among the subset of trucks. The accompanying table shows the slopes of the linear fit for each cycle. In this way, a 10% increase in weight produced a 6% increase in CO_2 mass rate (g/s) over the transient cycle, 1.8% increase in CO_2 mass rate over the creep cycle, and a 3.7% increase in CO_2 mass rate over the cruise cycle. Note that Idle cycle analysis is not relevant because emissions should be the same regardless of the weight if the vehicle is not moving.

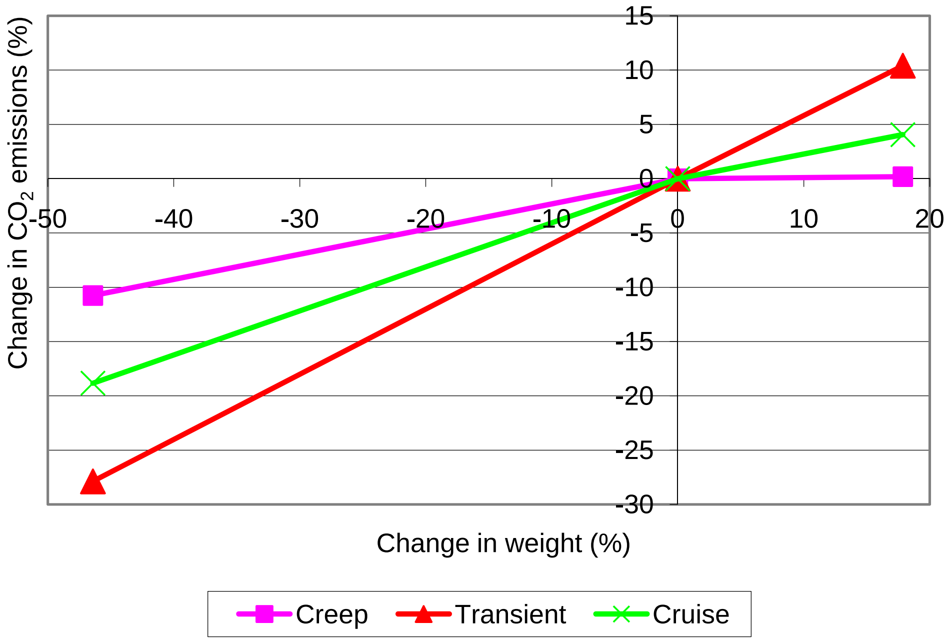
It can be seen that for each cycle there was an increase in the CO_2 emissions with increasing weight. The CO_2 emissions are a measure of the energy expended as they directly correspond to the fuel consumption of the vehicle. The relationship between test weight and CO_2 emissions is cycle dependant due to differences in transient behavior. Transient operation involves extra energy spent during accelerations, which is lost during decelerations (braking). This means that the Transient cycle will require the vehicle to expend higher energy with increasing weight than the Cruise or Creep cycles as it is seen in the values of slopes in the table accompanying Figure 33.

It is believed that the change in slope for the Cruise cycle is due to the fact that wind drag losses for heavy duty trucks become a substantial contribution only at sustained speeds of over 50 mph [11].

Table 19. Subset of CRC truck data for weight correction analysis.

E55CRC-(truck)	Vehicle model year	Vehicle Manufacturer	Engine Manufacture	Engine Model	Engine Power (hp)	Engine Disp. (Liter)	Odometer Reading (mile)
27	2000	Freightliner	Detroit	Series 60	500	12.7	420927
28	1999	Freightliner	Detroit	Series 60	500	12.7	645034
29	2000	Volvo	Cummins	1SX475ST2	450	14.9	120000
30	1999	Freightliner	Detroit	Series 60	500	12.7	138625
31	1998	Kenworth	Cummins	N14-460E+	460	14	587389
32	1992	Volvo	Caterpillar	3406B	280	14.6	595242
33	1985	Freightliner	Caterpillar	3406	310	14.6	988726

34	2004	Freightliner	Detroit	Series 60	500	14	19094
35	2001	Sterling	Detroit	Series 60	470	12.7	106377
36	2001	Peterbilt	Caterpillar	C-15	475	14.6	284553
38	2003	Volvo	Cummins	ISX	530	14.9	2829



Cycle	Slope
Creep	0.18
Transient	0.60
Cruise	0.37

Figure 33. percent change in CO_2 emissions per percent change in test weight

A more theoretical approach makes use of axle horsepower to correlate it with CO_2 emissions. Axle horsepower (AHP) is given by the road load equation for a level road, as follows:

$$AHP(hp) = mV\frac{dV}{dt} + \frac{1}{2}C_D A\rho V^3 + \mu mgV \qquad (28)$$

Where m is the mass of the vehicle (kg), *V* is the vehicle velocity (m/s), A is the frontal area of the vehicle (m^2), g is the acceleration due to gravity (m/s^2), C_D is the aerodynamic drag coefficient of the vehicle,µ is the tire rolling resistance coefficient, and ρ is the density of air (kg/m^3).

Chassis dynamometer test data can be used to obtain reliable correlations between axle horse power and CO_2 mass rate emissions of the form:

$$CO_2 = C_1 AHP + C_2$$

If the equation above (values of C_1 and C_2) remains reliable for a wide variety of truck applications, it is possible to apply these relationships to the axle power known for a given cycle (integration of instantaneous AHP over the test duration) and, therefore, to predict the total CO_2 mass arising from that cycle. Figure 34 shows variation of CO_2 emissions with axle power (test weight) for the Creep, Transient, and Cruise cycles. Again, the relationship between test weight and emissions will be cycle dependent; a highly transient cycle with high loads is likely to emphasize the effect of weight on CO_2 production in comparison to a steady-state operation with the same average speed. Conversely, if a test schedule contains long periods of idle, the idle CO_2 emissions contribution may become significant and will be weight insensitive [11].

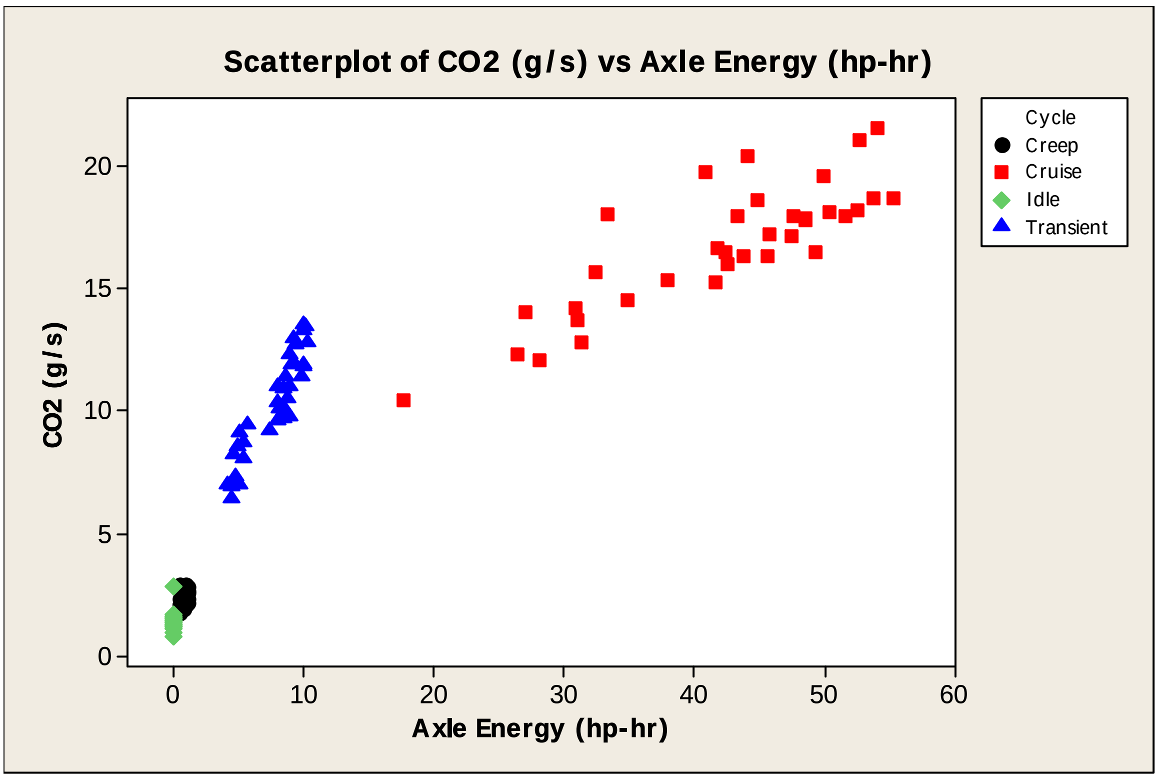


Figure 34. Variation of CO_2 emissions with axle power (test weight) for the Creep, Transient, and Cruise cycles.

Appendix B – Method of use

1. Identify fleet of vehicle subset from a fleet to be analyzed.
2. Obtain vehicle set driving characteristics. This could be either vehicle speed-time cycles or on-road activity. This is called “unseen” cycle.
3. Specify cycle metrics that can be used to translate fuel economy between cycles: Average velocity and average acceleration.
4. Calculate metrics for the selected vehicle set driving characteristics.
   Average Velocity: Summation of instantaneous velocity over number of data points.
   $$\bar{V} = \frac{\sum_{i=1}^{n} V_i}{n}$$
   Average Acceleration: Summation of instantaneous positive acceleration over number of data points. Instantaneous positive acceleration is calculated using a central differences scheme. Filtering of speed-time trace before calculation of acceleration is recommended.
   $$\overline{\frac{\partial V}{\partial t}} = \frac{\sum_{i=1}^{n} \frac{V_{i+1}-V_i}{\nabla t}}{n} \text{ when } V_{i+1} > V_i$$
5. Select representative chassis dynamometer baseline cycles.
   a. Idle cycle.
   b. Low average speed (50% to 100% of average speed of fleet), relatively high acceleration (100% to 150% of average acceleration of fleet) cycle.
   c. High average speed (more than 150% of average speed of fleet), relatively low acceleration cycle (50% to 100% of average acceleration of fleet) cycle.
6. Perform chassis dynamometer test for each vehicle/drivetrain/engine configuration. Obtain integrated CO_2 mass emissions, test duration, and distance traveled.
7. Pose a linear set of equations using average velocity and average acceleration of the three baseline cycles and the “unseen” cycle.
   $$w^{cycle\ a} speed^{cycle\ a} + w^{cycle\ b} speed^{cycle\ b} + w^{cycle\ c} speed^{cycle\ c} = speed^{\text{"unseen"}}$$
   $$w^{cycle\ a} accel^{cycle\ a} + w^{cycle\ b} accel^{cycle\ b} + w^{cycle\ c} accel^{cycle\ c} = accel^{\text{"unseen"}}$$
   $$w^{cycle\ a} + w^{cycle\ b} + w^{cycle\ c} = 1$$
8. Obtain the three weighting factors by solving the linear set of equations.
9. Apply the weighting factors to predict the vehicle “unseen” cycle’s CO_2 emissions.
   $${CO_2}^{\text{"unseen"}} = w^{cycle\ a} {CO_2}^{cycle\ a} + w^{cycle\ b} {CO_2}^{cycle\ b} + w^{cycle\ c} {CO_2}^{cycle\ c}$$
10. Convert the CO_2 mass rate emissions to fuel economy.
   $$Fuel\ Consumption \left(\frac{gal}{s}\right) = \frac{CO_2\left(\frac{g}{s}\right)}{10084}$$
   $$Fuel\ Economy\ (mpg) = \frac{Average\ Speed\ (mph)}{Fuel\ Consumption\left(\frac{gal}{s}\right) \times 3600}$$

Appendix C – Bus cycles

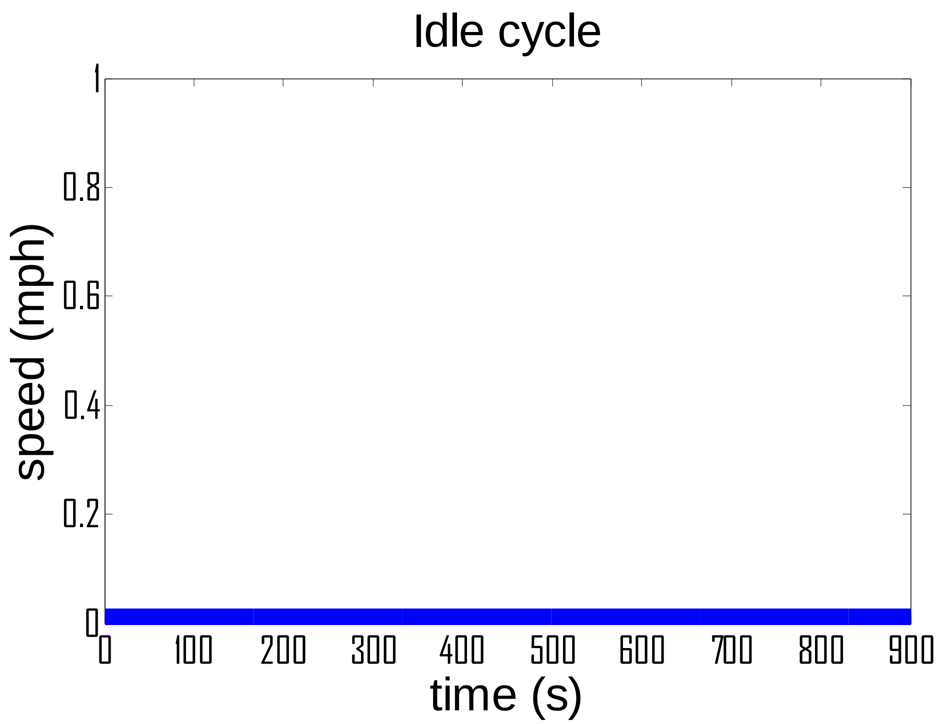


Figure 35. Idle cycle.

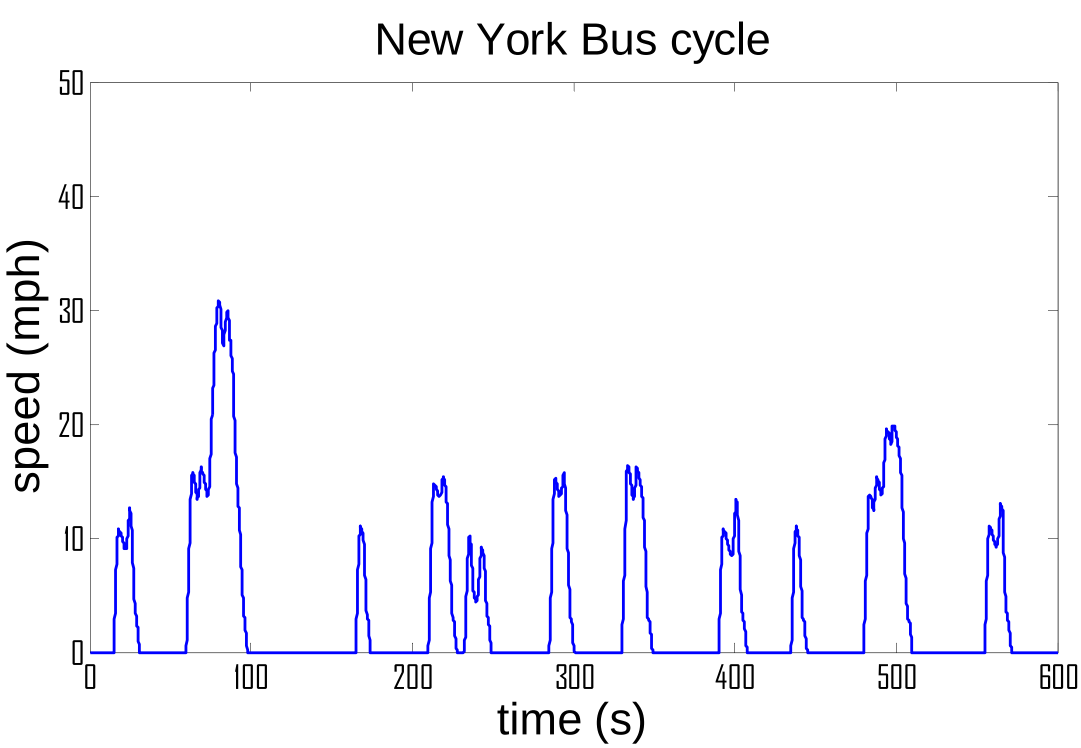


Figure 36. New York Bus cycle.

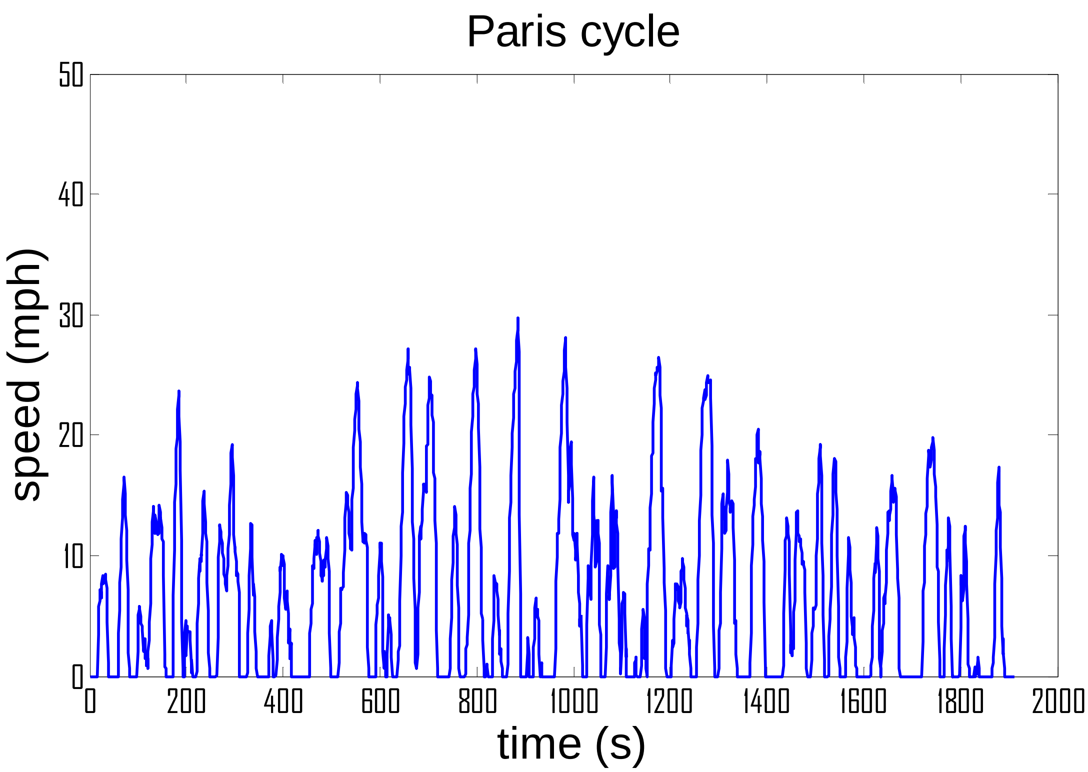


Figure 37. Paris cycle.

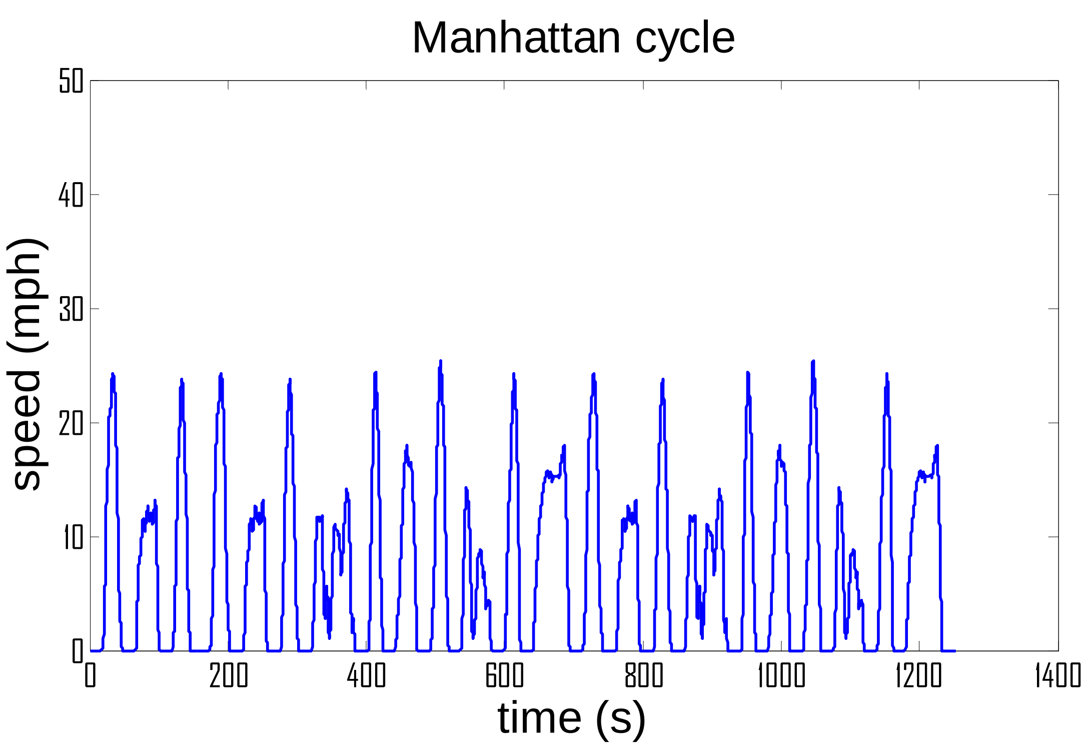


Figure 38. Manhattan cycle.

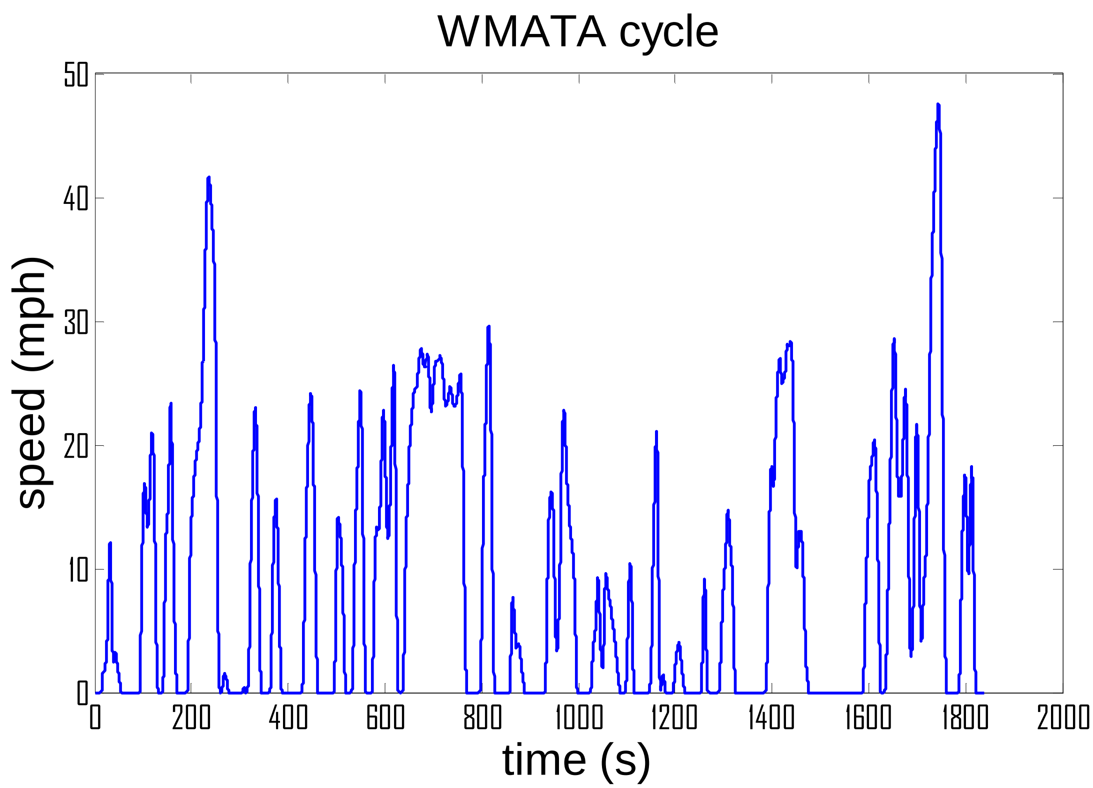


Figure 39. Washington Metro Transit Authority cycle.

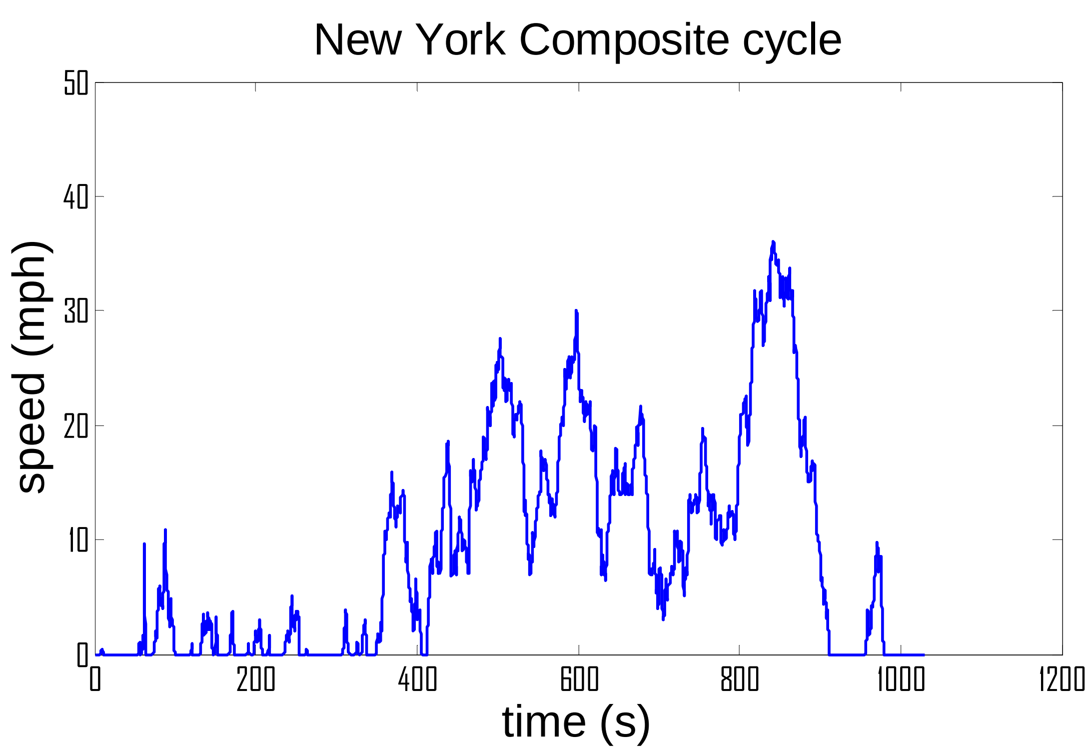


Figure 40. New York Composite cycle.

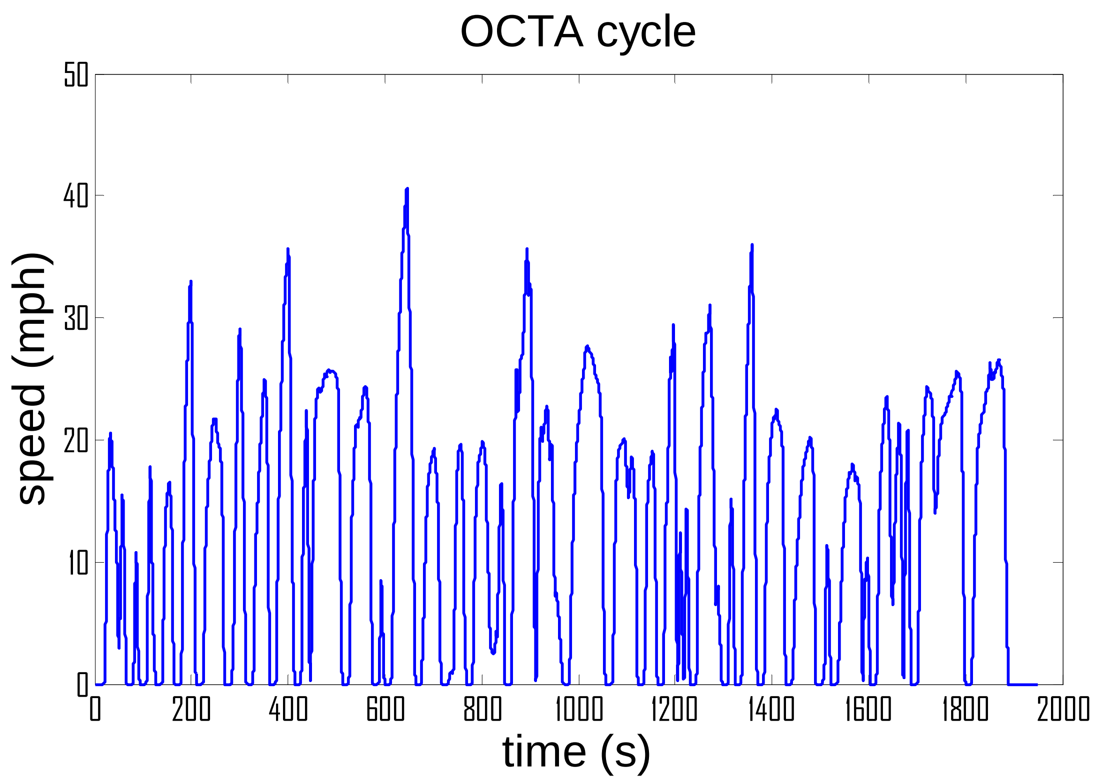


Figure 41. Orange County Transit Authority cycle.

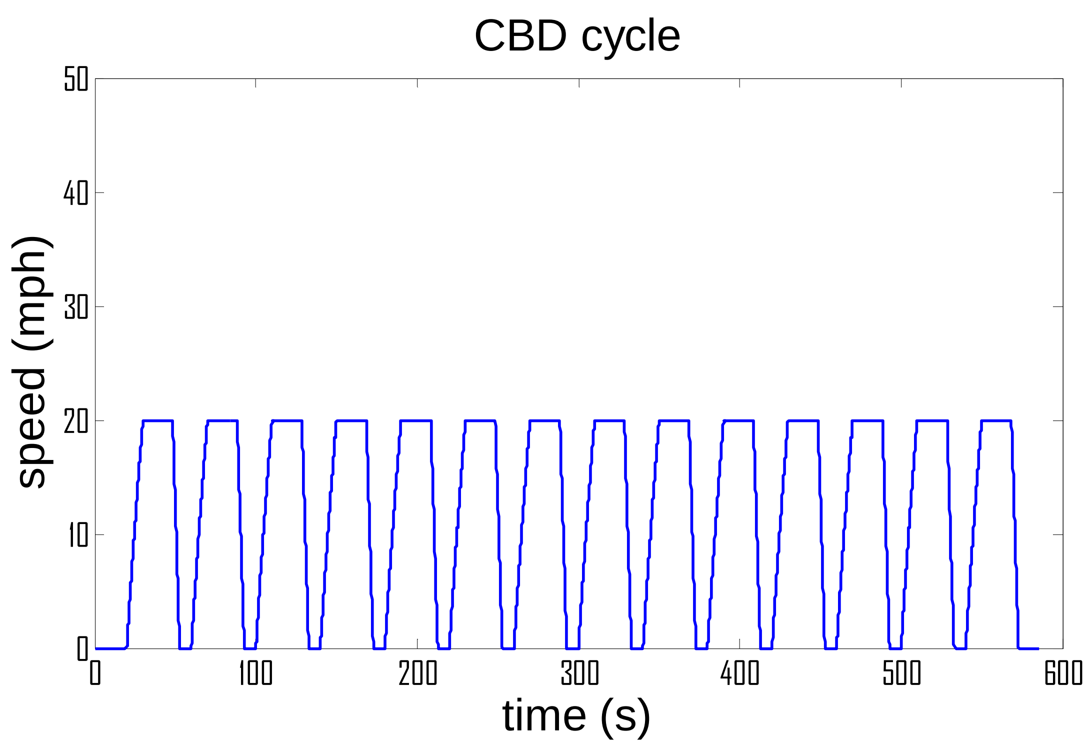


Figure 42. Central Business District cycle.

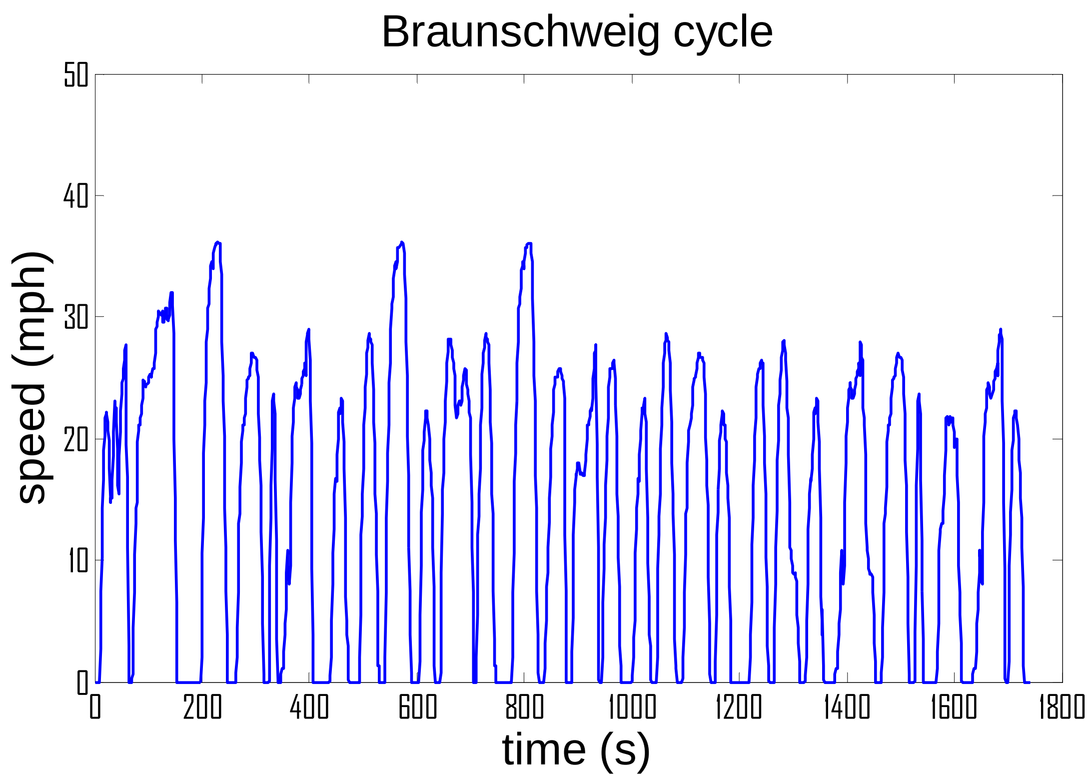


Figure 43. Braunschweig cycle.

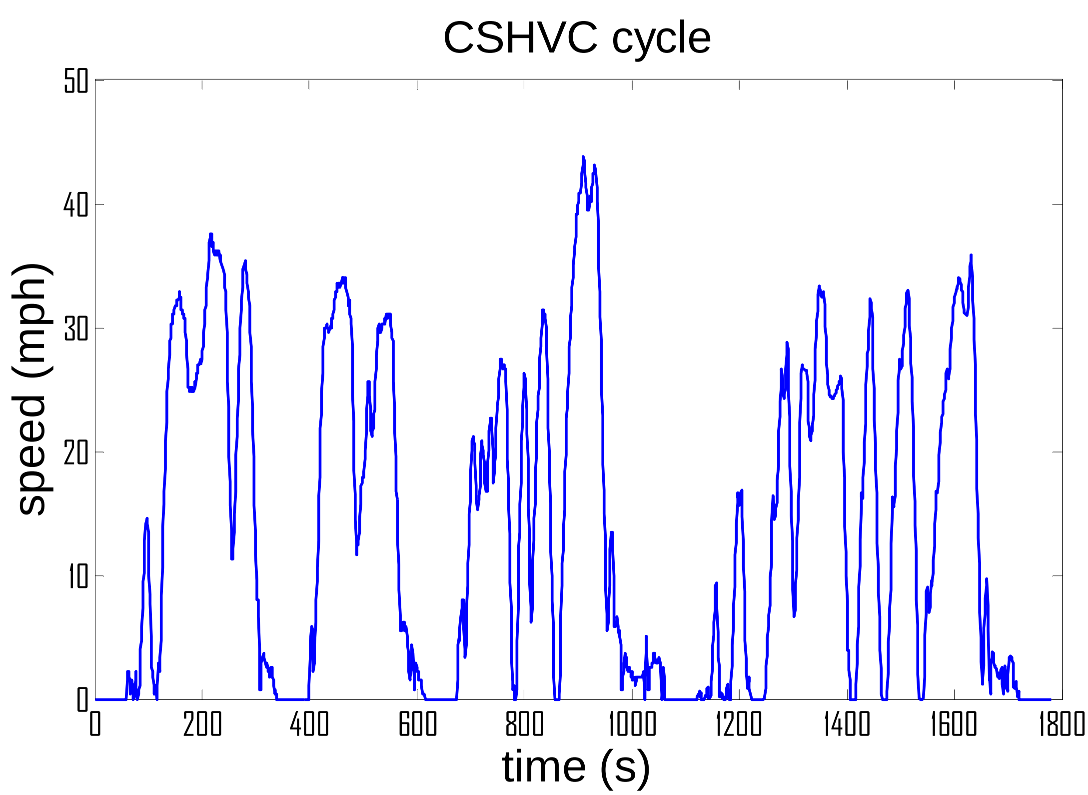


Figure 44. City Suburban Heavy Vehicle cycle.

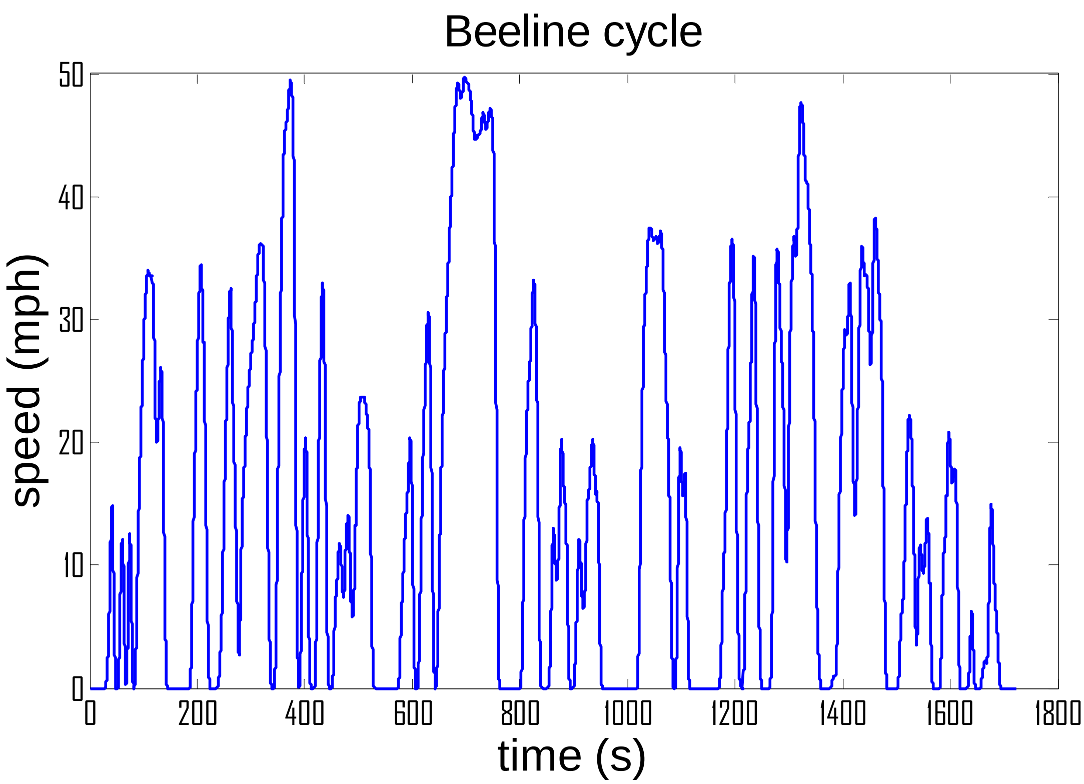


Figure 45. Beeline cycle.

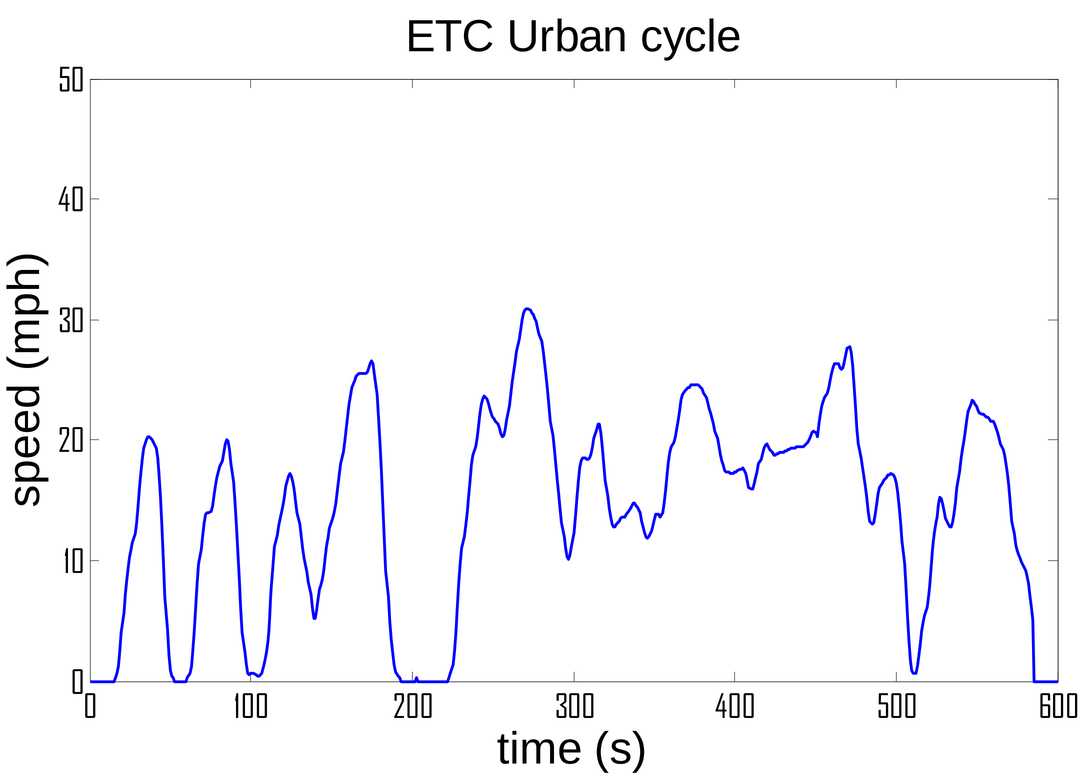


Figure 46. European Test Cycle Urban cycle.

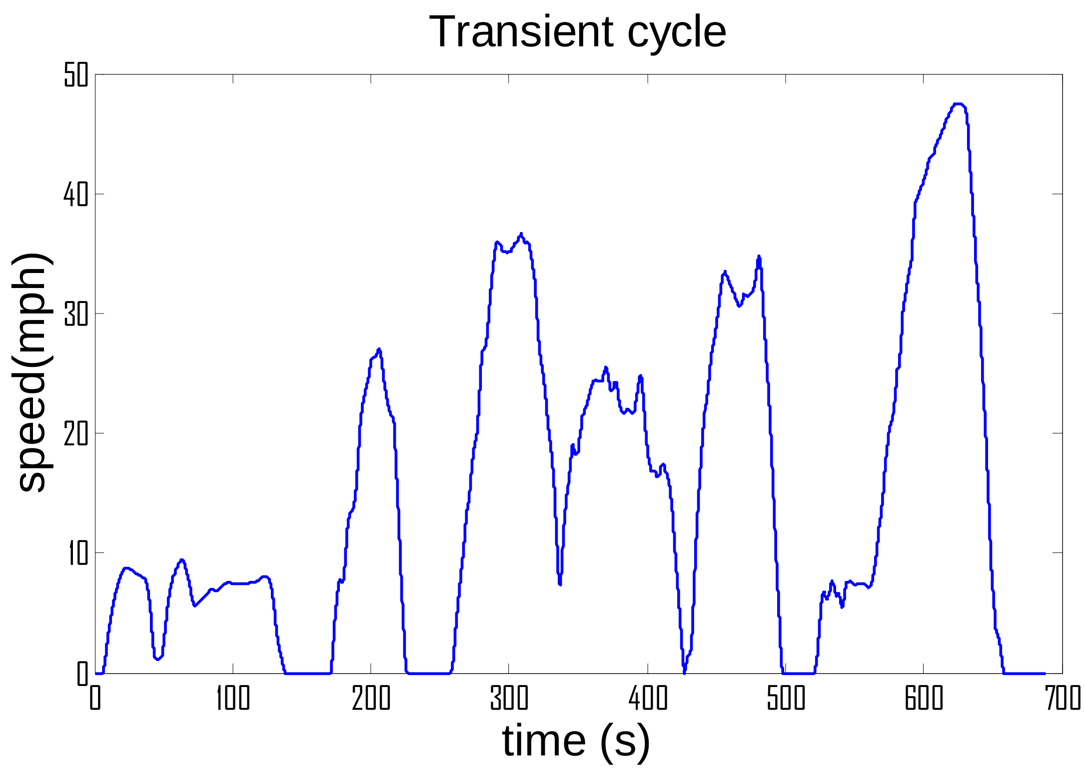


Figure 47. CARB Transient cycle.

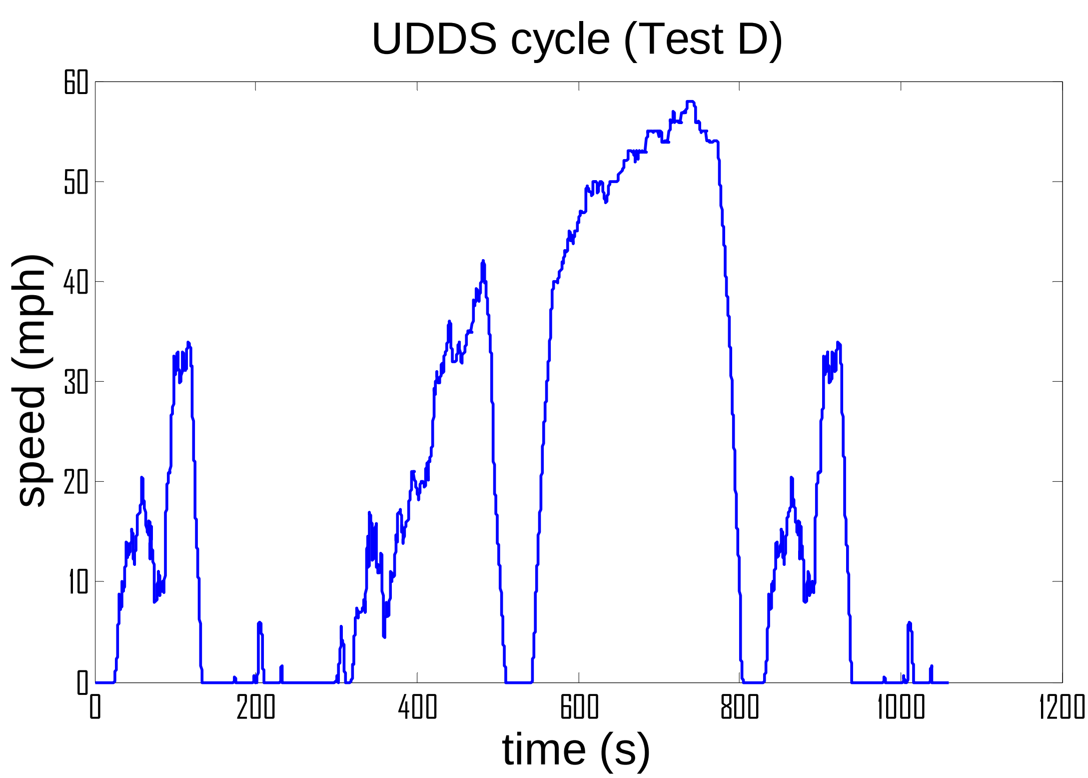


Figure 48. Urban Dynamometer Driving Schedule (Test_D cycle).

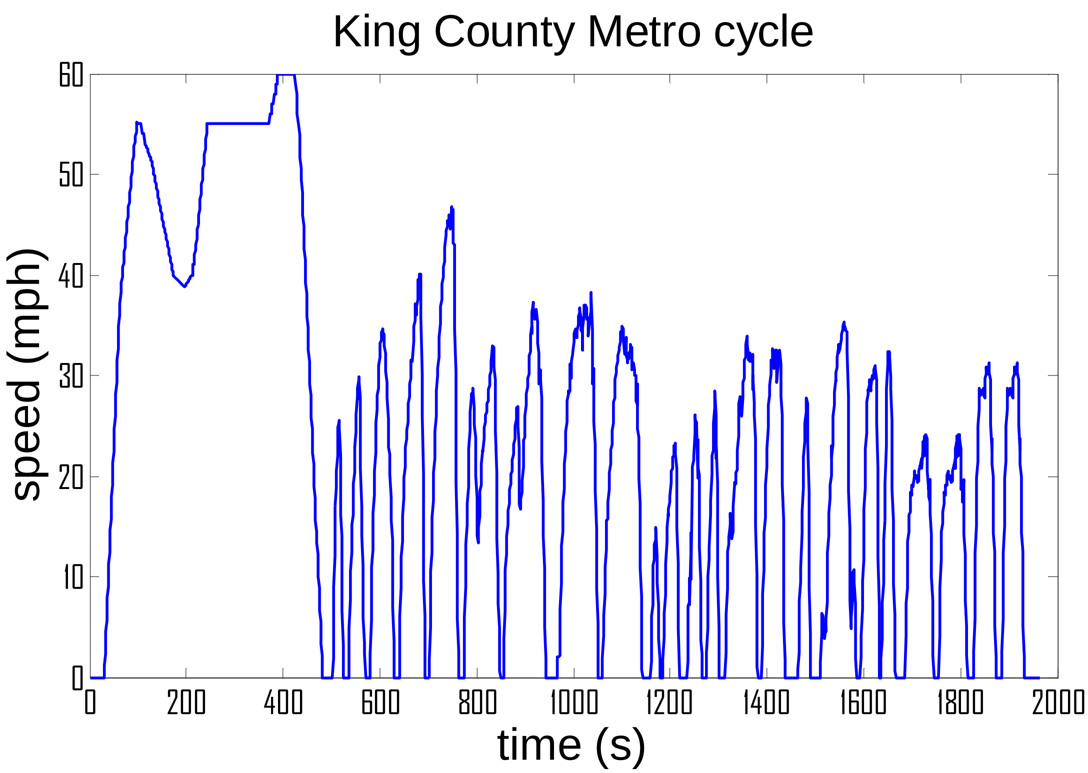


Figure 49. King County Metro cycle.

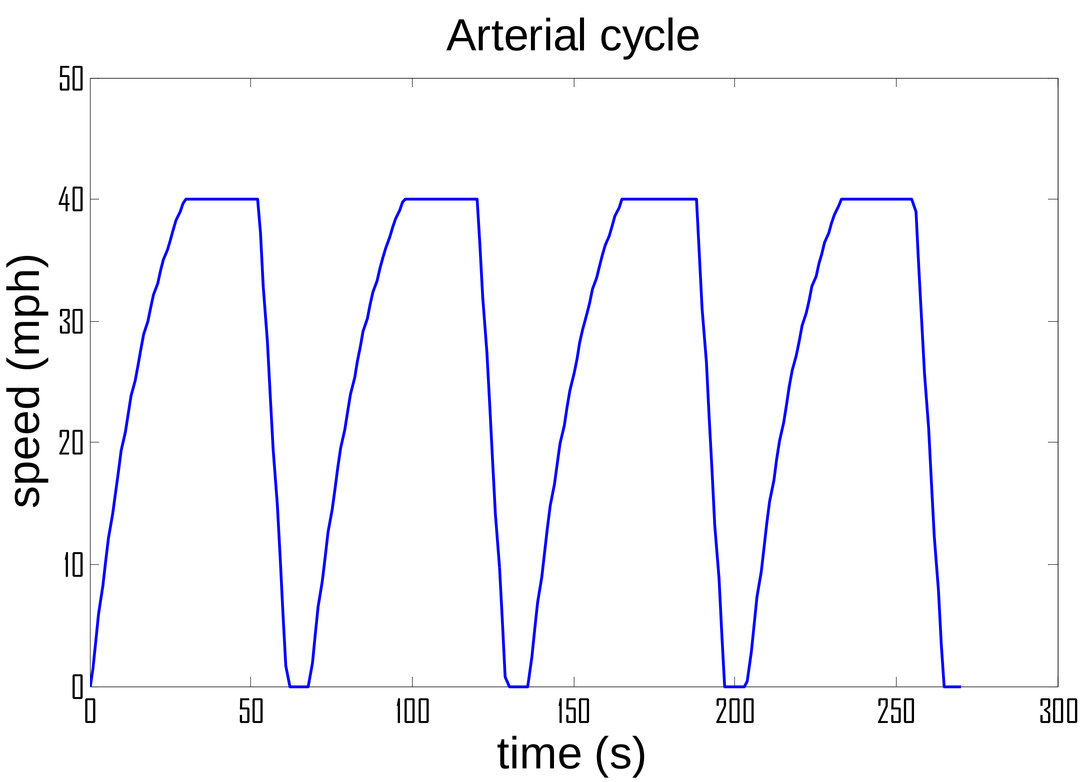


Figure 50. Arterial cycle.

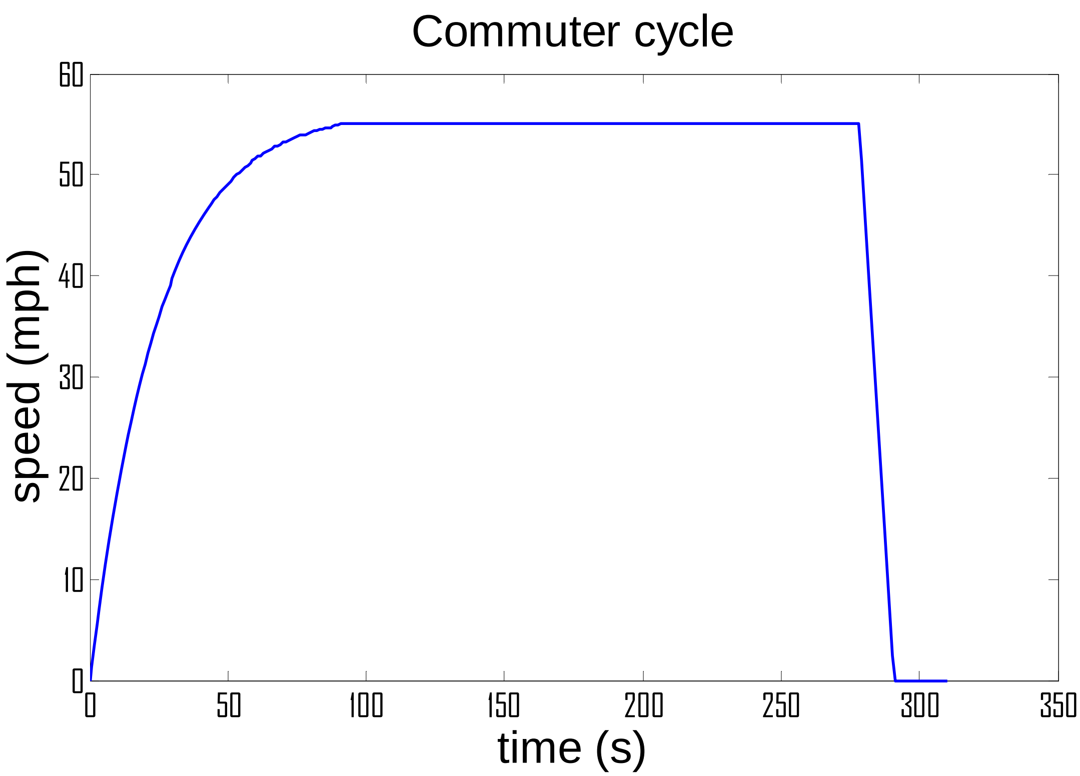


Figure 51. Commuter cycle.