Light-Duty Vehicle In-Use Fuel Economy Data Collection: Pilot Study

Report
Version 8

Prepared for:

International Council on Clean Transportation

Prepared by:

Eastern Research Group, Inc.

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Prepared for:

John German
Francisco Posada
International Council on Clean Transportation
1225 Eye Street, NW, Suite 900
Washington, DC 20005

Prepared by:

T.H. DeFries
M.A. Sabisch
S. Kishan
Eastern Research Group, Inc.
3508 Far West Blvd., Suite 210
Austin, TX 78731

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Executive Summary

ICCT has identified a need to determine the characteristics of instantaneous fuel economy (miles per gallon) tendencies of vehicles in today's U.S. fleet of light-duty vehicles. While several organizations agreed that a fuel economy study is important, they had questions and concerns about how a fuel economy project could be performed by collecting data using long-term instrumentation of private vehicles using OBD dataloggers. ICCT recognized that before a major nationwide instrumentation study of fuel economy characteristics could be undertaken, information addressing these concerns needed to be developed and evaluated. ICCT asked Eastern Research Group to conduct a pilot study to identify areas of concern and possible alternative solutions in four areas: vehicle sample structure and size, vehicle recruitment methodology, datalogger evaluations, and estimated project cost. This report is the result of that pilot study investigation.

Reasons for studying second-by-second fuel economy – As fossil fuel resources become scarcer and the demand for products derived from fossil fuels increases, pressure increases to develop new ways of improving vehicle fuel economy. Vehicle and engine manufacturers are continuously searching for new technologies that would produce higher fuel economy. Recent developments of gasoline/electric hybrid propulsion systems, gasoline direct injection fuel metering, and automatic transmissions with more than four gears are results of those efforts. To further improve the average fuel economy of the U.S. fleet, information about real-world driving behavior, the distribution of vehicle operating environments, and the influence of those factors on fuel economy would be a valuable resource for identifying the conditions under which today's technologies produce low fuel economies and high fuel economies. Information on real-world effectiveness of different technologies would be another potential valuable resource. To identify these conditions, measurements of second-by-second fuel economy rather than simply average fuel economy is required.

An additional reason for studying fuel economy is that vehicle emission rates are closely related to fuel consumption rate. The emission rates of most pollutants, including CO_2, a greenhouse gas, tend to be proportional to fuel consumption rate. Therefore, in general, vehicles or operating conditions that have high fuel consumption rates will also have high emission rates. As a result, the factors that affect fuel economy will also affect emissions.

Goal of the main study – ICCT would like to facilitate a nationwide study to investigate the fuel economy of light-duty vehicles. In this document, that national study will be called the main study. The goal of the main study would be to create a database of second-by-second fuel economies versus operating conditions for a sample set of vehicles. This dataset could be used in at a variety of ways. For example, it could be analyzed to determine how the fuel economies of current vehicles are influenced by different vehicle technologies as the vehicles are actually used. Another goal would be to determine the distribution of fuel economy influencing factors across the U.S. to help determine where technologies could further improve fuel economy and further reduce U.S. light-duty fleet emissions.

Main study project approach – While the objective of the main study is to investigate second-by-second fuel economy, from a technical perspective this really involves measuring fuel rate (mL/s) on a second-by-second basis, since fuel rate divided by speed (miles/hour) equals fuel economy (miles per gallon). Dynamometer testing, which is used to characterize average fuel economy of new vehicles, is not in-use testing and is of necessity a test of short duration and a single driving cycle. If in-use vehicles are instrumented using portable emissions measurement systems (PEMS), instantaneous fuel rates can be determined. However, obtaining PEMS data for a long duration is expensive, even for a single vehicle. A more feasible alternative is to use the OBD data stream for the newest light-duty vehicles in the fleet (approximately 1996 and newer vehicles) to gather information from which fuel rate measurements are reported or from which fuel rate could be calculated or estimated. For the main study, this alternative would involve obtaining OBD data for a one year period so that a complete dataset for each vehicle under operating conditions and trip behavior representative of all seasons would be obtained.

Pilot Project questions – As a result of the main study approach described above, the pilot project was undertaken to answer a number of questions about a potential main study, including:

- Would such a main study be possible? What are the hurdles?
- Does the OBD data stream provide information that could be used to measure or estimate fuel rate and vehicle speed and thus calculate fuel economy?
- Which vehicle/engine technologies provide better information than others?
- What accuracies for fuel rate could be expected?
- What factors are expected to affect fuel economy and what are alternative methods for measuring these factors?
- What are some options for logging, retrieving, and storing the OBD data stream information?
- What are some alternatives for the structure and size of a vehicle sample to be instrumented with OBD dataloggers?
- What are the options for identifying and recruiting potential participants?
- What are the estimated costs associated with recruiting vehicles, the datalogger, the cost of data transmission and other main cost sources?

Vehicle Sample: Structure and Size

A set of vehicles that is a subset of the U.S. fleet needs to be selected and instrumented to provide data for the main study. The vehicle sample needs to represent the range of vehicle technologies, operating environments, and driver attributes of the U.S. fleet. That objective could be accomplished with a randomly selected sample. However, such a sample would have a small number of vehicles for the less common technologies, environments, and driver attributes. For example, a random sample would have only about 1% diesel vehicles, about 2% hybrid vehicles, about 5% of vehicles home-based at altitudes greater than 5,000 feet, and a low percentage of newer technologies such as turbocharging, gasoline direct-injection, and transmissions with six or more gear ratios.

Another possible method to create the vehicle sample is to use a stratified, random approach. With this approach, certain strata of the U.S. fleet would be sampled at a higher or lower rate to increase or decrease the fraction of vehicles in the sample in those categories. The advantage of this approach is that a larger amount of data would be obtained for the less common strata so that a sufficient amount of information would be obtained from the instrumentation to provide a more reliable analysis of the trends for those strata. We recommend the stratified, random approach and proceed with the discussion with that approach in mind.

Design variables – The sample would be designed around a set of variables that are known or could possibly affect the fuel economy of vehicles. These variables fall into two categories. The time-dependent variables, which generally change from second to second, include the vehicle's operating environment and descriptors of the vehicle's internal operation as it responds to the operating environment and the driver. Operating environment includes road grade, altitude, and weather. Internal vehicle operation variables include vehicle speed, engine RPM, and A/C compressor status. Time-independent variables include vehicle technology, driver characteristics, general operating environment, and the individual vehicle. Driver characteristics include driver age, gender, socioeconomics, and aggressiveness. General operating environment variables include home-base altitude, home-base terrain (hilly vs. flat), and home-base climatic weather. Vehicle technologies include engine metering type (port fuel-injection, gasoline direct-injection, gasoline hybrid, port fuel-injection) and number of transmission gears. Individual vehicle characteristics include model year, make, model, and engine displacement.

Sample design approach – The vehicles for the sample can be selected only on variables that are known in advance for candidate vehicles. Because of this, vehicles cannot be selected based on time-dependent variables. The values of time-dependent variables for individual vehicles will be known only after the instrumentation data is obtained. Therefore, vehicles can be selected for the sample based only on vehicle technology, individual vehicle information, general operating environment, and driver characteristics. The time-independent variables can be split into two types for the purposes of designing and selecting the vehicle sample. The first is stratification variables. Stratification variables are the major variables that we want to investigate with the sample. Vehicles within each of the strata of these variables would be selected randomly. The second set of variables used to design the sample contains fleet representation variables. These are variables that are different from the stratification variables and are used to ensure that the vehicle sample is representative of the U.S. fleet.

A description of one possible sample structure – For this scenario, vehicles could be sampled from across the United States using three stratifying variables:

- **Propulsion System**. Propulsion system would be sampled with increased shares for diesel, gasoline direct-injection and hybrid technologies and reduced shares of port fuel-injection technology.
- **Fuel economy and environment label (FEEL) Highway MPG values**. The sample would be stratified with respect to this variable with enhanced fractions of low FEEL Highway MPG values and high FEEL Highway MPG values and suppressed fractions of moderate values. The FEEL Highway MPG values may be the best indicator of the general fuel economy tendency of the vehicle that can be

known in advance of vehicle selection. These values can be obtained for most year, make, and model vehicles from tables at fueleconomy.gov.

- **The ratio of FEEL City MPG to FEEL Highway MPG**. This ratio is a measure of the overall efficiency of the vehicle relative to the general tendency measured by the FEEL Highway MPG value. For example, vehicles will tend to have a low ratio if the vehicles are heavy compared to the power of their engines. Vehicles might be selected to have approximately equal numbers of vehicles in low, medium and high ratio categories.

Vehicles would be randomly selected within each combination of the three stratifying variables. However, the entire dataset would be subject to the constraint that the sample as a whole is approximately proportionately representative of the U.S. fleet in terms of 11 fleet characteristic variables: vehicle age, vehicle type, transmission type, manufacturer, total accumulated miles, driver age, driver socioeconomics, driver gender, altitude of base location, climatic precipitation, and climatic ambient temperature. As described in the body of this document, these 11 quantities can be determined or estimated for the U.S. fleet and for candidate vehicles for the sample.

Sample size – The size of the vehicle sample will affect the cost of the main study. In general, the sample should be large enough to provide the amount of data that is needed to answer the study questions. An estimate of the sample size needs to include consideration of what the resulting dataset will be used for and how it might be analyzed. Over a one year period, each instrumented vehicle would produce from one million to two million one-second observations on fuel economy, vehicle operation, and operating environment. Such a large set of data should be adequate to describe how the fuel economy of each vehicle depends on the variables of interest in the study. The analysis for each vehicle would determine how fuel economy depends on the speed, road grade, ambient temperature, wind, A/C compressor status, transmission gear, engine RPM, and so on. However, the dependence of fuel economy on each parameter will be different among the different individual vehicles in the sample because of the different designs used for vehicles and powertrains. Thus, across the vehicles in the sample, the coefficients that describe the dependences of individual fuel economies on the various factors will not converge to a single value for each factor but will make up of a distribution of values with one value for each vehicle in the sample. Consequently, larger sample sizes will better define the distribution of coefficients for each different factor under investigation in the analysis. Larger sample sizes will also provide more statistical assurance that driving behavior is representative of the fleet as a whole.

A measure of the distribution of coefficients for a fuel economy influencing factor, for example road grade, is the standard deviation of the distribution. The analysis in the report indicates that the standard deviation of arbitrary distributions of values of fuel economy influencing coefficients can be known with an uncertainty of about ±11% with a 200 vehicle sample or with an uncertainty of about ±8% with a 400 vehicle sample. Based on the analysis, we recommend that a sample no smaller than 200 vehicles should be used for the main study. Increasing the sample size beyond 200 vehicles will reduce the uncertainty in the distribution of the coefficients of fuel economy influencing factors, but substantially larger samples sizes are required to reduce the uncertainty just marginally. Modifying the number of stratification variables and/or the number of levels within each stratification variable would require changes in the sample size.

Participant Recruitment

The recruitment methodology for the main study needs to be developed to select a representative sample of the U.S. fleet that covers a range of vehicle technologies, operating environments, and driver behaviors. The report discusses the important components of vehicle recruiting – not to present a final methodology since many methodologies could be developed – but to discuss the different areas that any recruiting methodology would need to consider.

Source of participant candidates – Any vehicle sample that would be instrumented in the main study would need to address randomness and national coverage. Some aspect of randomness needs to be present in the selection of individual vehicles, and this could mean that vehicles are either selected randomly or that stratified random sampling could be used. National coverage is important so that the vehicles that are instrumented would be driven in different types of weather, on different types of terrain, and in both rural and urban areas. It is also needed to capture regional variances in driving behavior.

This study considered four alternative sources of participant candidates. The first source would be to conduct a household survey by telephone and online interviews to develop a pool of households and vehicles from which the vehicle sample would be collected. The second source considered was the panelists that certain companies such as Knowledge Network maintain to perform surveys. The panelists are carefully selected by these companies to be representative of the U.S. population. The third type of source for the participant pool would be from respondents of a separate on-going national household travel survey. Government and non-government organizations conduct such surveys to determine the travel habits of the U.S. population. The main study could tie into one of these on-going surveys to develop a participant pool. The fourth source is to use state vehicle registration databases to identify candidate vehicles. This approach would require that privacy concerns be worked out with at least several individual states.

Our analysis indicates that overall, the on-going household travel survey approach may be the most attractive. The organization sponsoring the household travel survey would already be interested in travel and, therefore, would likely also be interested in fuel economy trends. The data needs for creating the candidate pool of vehicles could be obtained by adding a few questions at the end of the household travel survey questionnaire and the groundwork would already have been provided by the survey operator. This source may be the least expensive of the four alternatives considered. Some of the information needed by the main study may already be requested by the survey operator. We could also expect a high willing-to-participate rate since the survey respondents who stay with the survey to the end of the questionnaire will likely be those who are most interested in participating in a fuel economy instrumentation study. The only downsides we see in using a household travel survey as a source of participants is that the survey sponsor has control over the time schedule for the survey and of ensuring an unbiased sample.

Description of recruitment methodology – The recruitment section of this report describes the process involved in selecting participants in the instrumentation study and maintaining their participation for the instrumentation phase. First, the national household survey respondents would be asked if they would be willing to participate in a fuel economy instrumentation study and initial information about their vehicles and demographics would be obtained. An analysis of the candidates would be performed to compare with the vehicle sample structure and size described previously. Certain households and vehicles would be targeted using online and telephone recruitment to form a participant pool. The recruitment would collect additional information about vehicle base location and driver demographics. The instrumented sample would then be selected from the participant pool. Dataloggers would be sent or otherwise installed on the participating vehicles and the relationship between the study participants and the main study project team would be maintained for the one-year instrumentation period to ensure that quality data is obtained from the targeted number of vehicles in the main study.

Tools for recruitment and participant maintenance – A variety of tools would be used to recruit and maintain the instrumented vehicle sample during the presumed one-year data collection period. These tools would include an incentive package, a project website, an advanced notification package, telephone recruitment tools, datalogger assistance, and participant management tools.

Since the study would continue over an extended period of time, incentives should regularly be provided to study participants to encourage their continued participation. We know from experience that in long-term studies such as the main study, offering staggered incentives for completing certain tasks or assignments on a predetermined schedule also works well to retain participants. This report discusses five incentive package ideas: monetary, gift cards, games on the study website, free American Automobile Association membership, and a vehicle data report.

An advanced notification package would be sent to participation candidates who have been selected for participation to gain their cooperation. The package for the main study would include, for example, an introductory letter, a study brochure, instructions and passwords for participating in the online recruitment interview, or alternatively for participation in a telephone interview. The materials would describe who is conducting the main study and why, the incentives that are being offered to participants, what the participant would be required to do.

A project website would be set up to maintain the main study's communications between the main study project team and survey participants. The project website would include study information for the participants, FAQs about the study, how the participants can contact the project team, information for the public.

Because only about 20% of households that receive the advanced notification package typically complete online recruitment, the remaining 80% of targeted households would need to be recruited by telephone calls. Telephone interviewers can use the online recruitment tool to recruit targeted households during the telephone interviews. A series of "hot buttons" would be available to the interviewer to guide the interview through the recruitment web page to ensure complete collection of all critical data elements.

We anticipate that OBD dataloggers will be sent to recruitment households to be installed by the owner on the recruited vehicle. Ideally, the datalogger will be designed so that most vehicle owners can perform the installation themselves. However, in some cases, data owners may require assistance. In these cases, local vendors would be needed to install the dataloggers for the owners.

Several different project management tools will be needed to maintain participation of the vehicles in the study. At least four contacts with participants should be made during the study but they should be short and simple and may be administered by mail with web and telephone options according to the participant's preference. The responses would be tracked so that a lack of online or mail response would result in a telephone contact. The challenge of recruiting and retaining participants involves not only motivating them to participate, but also not "over educating" them on the transportation issues which can inappropriately bias responses. After a candidate initially accepts participation in the study, a principle problem of panel research is attrition. The recommended design would be structured to minimize that attrition by several activities.

Validation of vehicle recruitment methodology – Recruitment methodology validation would be performed early in the main study using two different activities. The first is cognitive testing which occurs on the draft recruitment materials using a small group of people to evaluate the understanding of those materials. The second is a shake-down process that would occur during the beginning of main study as initial candidates are slowly recruited for the study. During the shake-down period, the recruiting methodology can be evaluated and modified based on the initial findings of actual participant candidates and participants.

Datalogger Evaluations

One objective of this pilot study was to procure or develop a datalogging system to collect and record OBDII engine and vehicle operating data that could be used to calculate in-use second-by-second fuel rate estimates under all operating conditions, for up to one year in duration. A small, unobtrusive system was sought for this study that could be used on 1996 and newer light-duty gasoline, diesel, and hybrid vehicles, could be installed by the study participants themselves, and would automatically initiate recording and sleep modes. Collection of SAE J1979 parameters (standard PIDs) and some manufacturer-specific parameters (enhanced PIDs, for data such as hybrid battery state of charge, air conditioning compressor status, and vehicle fuel rate, as available) was required. Dataloggers were evaluated that could either store all the data on the datalogger or broadcast the data (via a cellular modem) to an internet-based server.

The method to read or measure fuel consumption rates through the OBD port varies by vehicle make, model, and engine. Many gasoline-powered vehicles directly report the mass of air entering the engine as measured by the engine's mass air flow sensor (this data is broadcast as a standard PID). For these vehicles, the reported mass of air provided to the engine can be used in the gasoline combustion equation to calculate the amount of fuel required for stoichiometric engine operation. Fuel rates during non-stoichiometric operation may be calculated using the ratio of actual air provided to an engine to the theoretical air required for stoichiometric combustion (this ratio is sometimes referred to as lambda), which is reported as a standard PID for vehicles with wide-band oxygen sensors. However, there are a number of situations for which the above approach cannot be used. These include:

- Operation of vehicles that do not broadcast mass air flow and/or lambda,

- Operation of diesel vehicles, which employ different air / fuel management strategies and which do not operate stoichiometrically, and
- Vehicle operation during open loop fuel control (i.e., cold start, fuel cut-off, or power enrichment mode), if lambda is not broadcast during these non-stoichiometric periods.

For these situations, different methods for calculating the instantaneous fuel rate using additional standard PIDs (such as manifold absolute pressure, commanded equivalence ratio, narrow-band oxygen sensor voltage, engine speed, calculated load, long-term or short-term fuel trims, or other PIDs) might be required, or collection of enhanced PIDs (such as engine fuel rate, injector fuel rate, or injector duration) might be required. In addition, some late model vehicles broadcast engine fuel rate as a standard PID, which may be used when available. Details of the recommended measurement strategies based on the type of vehicle and operation is provided in the study report.

Datalogger research and selection – ERG performed market research to identify one or more dataloggers that most closely met the requirements specified by ICCT for this project. Information was gathered on products offered by more than 40 companies to identify candidate loggers for this project, and of those, a more comprehensive review was given to eleven of those candidates. Each of the eleven candidates was ranked based on suitability for use in the main study, limitations of use in the main study, and price range. Based on this review, two units were selected for in-use testing during this pilot study: the HEM Data DAWN Mini and the LiveDrive i2d.

Both units were acquired and tested to assess suitability for use in the main study. However, ERG was unable to thoroughly evaluate the LiveDrive i2d unit, as it was undergoing development during the evaluation period, and some forthcoming features were not functional on our unit during the period of evaluation. In particular, the i2d datalogging system did not provide instantaneous fuel rate estimates, nor did it allow the user to modify which standard PIDs would be recorded by the datalogger, so ERG was unable to configure the i2d logger to collect all the standard OBD data that would be needed to calculate instantaneous fuel rate estimates. Consequently, the HEM Data DAWN Mini datalogger was used for the fuel rate validation testing performed for this study.

Datalogger Costs – A wide price range was seen between the HEM Data DAWN and LiveDrive i2d loggers. Although the HEM Data costs were largely dependent on which features were selected for DAWN logger, ERG's loaded cost for the HEM Data DAWN logger was approximately[1] \$1200 vs. approximately \$200 for the LiveDrive i2d logger, both with GPS and cellular capability.

[1] The per-unit price of the HEM Data DAWN logger depends greatly on the options desired and the quantity ordered.

Validation of Fuel Rates Obtained by Dataloggers

After datalogger selections were made, the dataloggers were evaluated using comparisons of second-by-second fuel rates obtained in three datasets:

1. **Standard OBD PIDs[2] vs. PEMS** – A cursory comparison of fuel rates on 19 vehicles,
2. **Standard OBD PIDs vs. Enhanced OBD PIDs[3]** – A comparison of fuel rates on one MAF/wide-band O2 sensor vehicle and one hybrid vehicle,
3. **Standard OBD PIDs vs. Dynamometer-Measured Fuel Rates** – A comparison of fuel rates on one GDI/narrow-band O2 sensor vehicle.

Validation using Kansas City PEMS Data – Second-by-second fuel rate results from portable emissions measurement system (PEMS) data from the U.S. EPA's Kansas City Light-Duty Vehicle Study were compared with fuel rate estimates from standard OBDII PID data (standard SAE J1979 MAF / fuel trim) from the same study.

The second-by-second data was obtained from dynamometer testing over the LA92 test cycle and from on-road PEMS testing. The PEMS unit calculated fuel rate from measured exhaust mass flow and exhaust concentrations and simultaneously collected selected standard OBDII parameters including mass airflow, engine RPM, throttle position, engine coolant temperature, air intake temperature, and bank one fuel trim data. The Kansas City PEMS units did not collect oxygen sensor or lambda sensor data, which limits our ability to adjust OBDII based fuel economy estimates for non-stoichiometric operation.

For the 19 selected vehicles for this analysis, 85,000 seconds of operation when the engine was on and the OBD and PEMS units were collecting data were obtained. We calculated the stoichiometric fuel rate using the OBD-reported mass air flow, an assumed specific gravity

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[2] An OBDII PID is a second generation on-board diagnostic parameter identification, which is commonly abbreviated as PID. This is a code that is used by a scan tool or datalogger to request specific information from a vehicle. SAE J1962 describes the OBDII-compliant hardware. SAE J1979 defines the “standard” PIDs that may be broadcast by a vehicle and how to translate and calculate the responses to those PID requests. Although all 1996 and newer light-duty (<8500 lbs) vehicles and some newer medium duty vehicles and heavy-duty vehicles are required to be OBDII compliant (they are required to have SAE J1962-compliant hardware and be SAE J1979 compliant), not all SAE J1979 PIDs are required to be broadcast by a vehicle (vehicle manufacturers may choose which subset of PIDs to broadcast based on the vehicle's powertrain technology). The subset of standard PIDs broadcast by a manufacturer can be decoded / calculated using information provided in SAE J1979.

[3] Vehicle manufacturers can, and do, provide additional operational and diagnostic information data that is specific to each manufacturer. The information needed for a scan tool or datalogger to request, decode, and translate these “enhanced parameter IDs, ” or “enhanced PIDs, ” is manufacturer-specific and is not provided in SAE specifications. The information needed to collect and translate enhanced PIDs must be obtained from vehicle manufacturers, although some manufacturers may provide information through a central source such as the Equipment and Tool Institute. The enhanced PIDs available by manufacturer vary. Some enhanced PIDs of interest in this study include hybrid vehicle battery state of charge, air conditioning compressor status, and some indicator of fuel rate (e.g., fuel injection timing / duration, fuel injected mass / volume per cylinder rotation, or perhaps some form of calculated fuel rate).

for the fuel, and an assumed stoichiometric air-fuel ratio. The PEMS unit reported fuel rate based on measured emissions concentrations and measured exhaust mass flow rate. The OBD data and the PEMS data were time aligned based on the calculated fuel rates. However, no effort was made to account for any diffusion effect that might influence the PEMS fuel rate time series.

Analysis of the calculated fuel rates showed that, in general, the OBD fuel rate was directly proportional to the measured PEMS fuel rate. However, many individual one-second values deviated from the general trend. An analysis of engine operating conditions that may have been non-stoichiometric could not explain these deviations.

Comparison of standard versus enhanced PID fuel rate estimates – Second-by-second fuel rate estimates calculated from standard PIDs were compared with fuel rate estimates calculated using an enhanced PID (OEM fuel injector fuel rate) data from the same test. This comparison was made for two vehicles, a 2012 Toyota Camry and a 2011 Toyota Prius, both with 4-cylinder engines equipped with mass air flow sensors and wide-band oxygen sensors. For each data set, mass air flow and lambda were the standard PIDs used to estimate fuel rate, while injector fuel rate was the enhanced PID used for the engine's fuel rate estimate. The injector fuel rate was converted to engine fuel rate using the engine speed, accounting for a 4-cylinder, 4-stroke engine, and performing unit conversions as needed.

For the Camry, the cumulative mass air flow-based fuel rate was approximately 13 % lower than the injector-based value, while the Prius' mass-air-flow-based fuel rate was approximately 3 % lower than the injector-based value. For both the Camry and the Prius, the instantaneous differences between the two fuel rates were much greater than the cumulative differences, primarily because the deviations tended to occur at low fuel rate transients that did not contribute significantly to the overall cumulative fuel usage but where the relative (percentage) differences tended to be quite large. For the Camry, the average of the percent differences between the mass air flow-based fuel rate and the injector fuel rate was 151%, and for the Prius, this average of percent differences was 22%. The coefficient of determination between the Camry's mass air flow-based fuel rate and the injector fuel rate was r^2=0.81, and for the Prius it was r^2=0.98.

For the Camry, most of the discrepancies (nearly 80%) occurred at times when the vehicle was coasting or slowing, and during these times the injector fuel rate remained significantly higher than the MAF fuel rate.[4] A review of the data suggests the MAF/lambda-based fuel rate was reasonable, while the injector-based fuel rate appeared incorrect during these discrepancies. The specific reason for this discrepancy was not identified, although it appears the vehicle may have been under deceleration-based fuel cut during these times. For the Prius, both the mass air flow and injector-based fuel rates appeared reasonable throughout operation, and most of the differences between these two rates appeared to be a result of comparing two different and rapidly-changing signals with different rise and fall rates over quickly-fluctuating transients.

[4] This is an important finding since it suggests that fuel rates based on OBD information may not always be accurate. Before a main study is undertaken, a prudent next step would be to compare fuel rates calculated from OBD information against dyno-measured fuel rates for a variety of vehicles and technologies to determine the extent and vehicle/engine operating conditions of fuel rate disagreements.

Validation using Dynamometer – One set of data was collected to compare fuel rate calculated from OBD-generated information with measured fuel rate from dynamometer measurements. A 2009 Saturn Outlook with gasoline direct-injection, mass air flow fuel metering, and a narrow-band oxygen sensor was tested on a chassis dynamometer while driving the HFET, US06, and FTP75 test cycles at 70°F ambient temperature. The dynamometer instrumentation measured exhaust flow rate and emissions concentrations from which mass fuel rate was calculated by carbon balance. During the testing, the HEM Data logger collected second-by-second standard PID OBD parameters.

The dynamometer and OBD datasets were time aligned using the dynamometer and OBD speed values. Dynamometer volumetric fuel rate was calculated from dynamometer mass fuel rate and fuel density. OBD volumetric fuel rate was calculated from the reported OBD mass airflow, the stoichiometric air/fuel ratio, and the fuel density.

After final time alignment, examination of the data revealed three trends in the dynamometer and OBD fuel rate time series:

1. In general, the shape of the dynamometer and OBD fuel rate time series agreed. However, the OBD time series had more high frequency fuel consumption variation than the dynamometer-measured fuel rate time series. That is, the dynamometer fuel rate time series appeared to be smooth in comparison with the OBD fuel rate time series.

2. Fuel cutoff events, which occurred during long decelerations, were indicated by the OBD commanded equivalence ratio PID with values just below 2.0. The dynamometer-measured fuel rate during fuel cutoffs exhibited exponential decays rather than flat bottom wells.

3. The one cold start, which occurred at the beginning of Bag 1 of the FTP75 cycle at an ambient temperature of about 70°F, was indicated by the OBD commanded equivalence ratio PID with values near 1.025.

A neural network model was used to confirm that the OBD mass air flow PID and the OBD commanded equivalence ratio PID contained sufficient information to predict the dynamometer measured fuel rate during stoichiometric operation, the six fuel cutoff events, and the one cold start. The model predicted the dyne-measured fuel rate with an r^2 of 0.993 and a standard deviation of 0.12 mL/s, which is 2% of the maximum observed fuel rate for the vehicle and 25% of the observed fuel rate at idle.

While the OBD commanded equivalence ratio PID was able to indicate when the cold start occurred, the value of that variable (1.025) during the 70°F cold start did not reflect the observed actual lambda, which was about 1.4. This suggests that at least for this vehicle, which had a narrow-band oxygen sensor, the standard OBD PIDs were able to predict the fuel rate during stoichiometric operation and fuel cut offs but were able to only indicate when enrichment or enleanment events occurred but not the value of lambda. This suggests that narrow-band oxygen sensors may not be adequate to calculate fuel consumption when enrichment occurs during cold starts and high load operation.

Conclusions

Overall, the pilot study indicates that a main study, which would be made up of preparation, collection, and processing sub-studies, could be performed with the goal of collecting one year of 1 Hz data on fuel economy and the factors that influence fuel economy for a moderately-sized sample of the U.S. light-duty fleet. The analysis indicates that, at this time, a full-blown effort to acquire accurate fuel economy data on any 1996 and newer vehicle of any technology would be an expensive undertaking. The tables below show that the estimated cost to acquire one year of second-by-second data is from about $3,700 to $7,200 per vehicle for a 200-vehicle sample and is from about $2,600 to $5,000 per vehicle for an 800-vehicle sample, plus pre- and post-processing costs of about $1,300 per vehicle for a 200-vehicle sample and $400 per vehicle for an 800-vehicle sample.

Estimated Project Costs for 200- and 800-Vehicle Scenarios

	Task	Detail	200 Vehicles		800 vehicles	
			Low	High	Low	High
Prepare	Preparation for Main Study	Sample/Recruitment Design	44,000	44,000	44,000	44,000
		Datalogger Design	79,000	79,000	79,000	79,000
		Total	**123,000**	**123,000**	**123,000**	**123,000**
		Preparation Total	**123,000**	**123,000**	**123,000**	**123,000**

	Task	Detail	200 Vehicles Low	200 Vehicles High	800 vehicles Low	800 vehicles High
Collect	Recruitment and Sampling	Fleet characterization and filtering	84,000	84,000	192,000	192,000
		Participant interaction and management	26,000	26,000	84,000	84,000
		Sources of drivers/vehicles	11,000	253,000	44,000	495,000
		Total	**121,000**	**363,000**	**320,000**	**771,000**
	Data Collection	Tailoring for each vehicle	40,000	40,000	160,000	160,000
		Datalogger logistics + maintenance	172,000	266,000	687,000	826,000
		Data management	0	38,000	0	154,000
		Incentives	37,000	154,000	147,000	617,000
		Total	**249,000**	**498,000**	**994,000**	**1,757,000**
	Datalogger	Datalogger basic hardware	234,000	234,000	607,000	607,000
		Cellular data + hardware	0	201,000	0	767,000
		Enhanced PID costs	134,000	134,000	134,000	134,000
		Total	**368,000**	**569,000**	**741,000**	**1,508,000**
		Data Collection Total	**738,000**	**1,430,000**	**2,055,000**	**4,036,000**

	Task	Detail	200 Vehicles Low	200 Vehicles High	800 vehicles Low	800 vehicles High
Process	Data Processing	Acquire/Link associated data	31,000	31,000	31,000	31,000
		Presentation of data	83,000	83,000	123,000	123,000
		Data archiving	5,000	24,000	5,000	24,000
		Total	**119,000**	**138,000**	**159,000**	**178,000**
		Data Processing Total	**119,000**	**138,000**	**159,000**	**178,000**

The areas of sample design and vehicle recruitment appear to have no technical challenges that cannot be met. Costs for these areas are substantial; however, opportunities probably exist for cost reductions through collaboration and cost-sharing with organizations that have related interests in transportation, vehicle usage, vehicle maintenance, and emissions. This leaves primarily three areas where challenges remain: OBD dataloggers, OBD data issues, and fuel rate calculated from OBD data.

Although it is moderately straightforward to obtain OBD-based average fuel rate estimates for a large number of on-road light-duty vehicles, it can be significantly more challenging (and costly) to obtain moderately accurate instantaneous (second-by-second) estimates, due to large variations in instantaneous fuel rates and the challenges of quantifying fuel rates during periods of non-stoichiometric operation for vehicles that do not have wide-band sensors that directly output lambda.

Additional work on calculating accurate fuel rates is needed before undertaking a study that includes vehicles with narrow-band oxygen sensors. Even for vehicles with wide-band sensors, instantaneous fuel rate estimates can be inaccurate if wide-band lambda is not reported during open-loop operation (such as during cold starts, fuel cut, or enrichment operation).

Similarly, mass air flow signals are available for the majority of 1996 and newer light-duty gasoline-powered on-road vehicles in the U.S. A study focused on these vehicles will be more affordable and likely have more accurate results than a study that includes all 1996 and newer light-duty vehicles, including those that do not broadcast a mass air flow signal and non-stoichiometric vehicles such as diesels. However, diesel vehicles and vehicles that do not broadcast a mass air flow signal likely comprise 25% to 50% of the 1996 and newer on-road fleet in the U.S., so a significant portion of the fleet is excluded by excluding these vehicles. Ultimately, the intended goals of the study will guide the decisions about whether instantaneous fuel rate results and the level of fleet penetration – in terms of both the vehicle types that can be instrumented and the amount of enhanced PID data collected – justify the costs.

Because of the diversity of vehicle technologies, only a subset of standard PIDs is broadcast for any individual vehicle, and this list of PIDs differs from vehicle to vehicle. Although it may be possible to have a "generic" PID-request configuration for all dataloggers to be used in the study, knowing which PIDs are broadcast for any specific vehicle prior to beginning a main study would be beneficial in optimizing vehicle-specific datalogger configurations. This will help ensure the optimal data is collected for each vehicle and minimize the possibility of reduced sampling rates resulting from oversampling, that is, requesting more PIDs than can be collected on a 1 Hz basis.

The collection of some enhanced PIDs, such as hybrid battery state of charge and air conditioning compressor status, will be necessary to achieve some potential main study objectives. Enhanced PIDs directly reporting fuel rate would also be necessary in order to include diesels and gasoline vehicles without mass airflow or air/fuel outputs. Because of the vast differences in types and availability of enhanced PIDs among vehicle manufacturers, costs and feasibility for acquiring enhanced PIDs varies greatly from manufacturer to manufacturer. So, although it is reasonable to expect that enhanced PIDs such as hybrid battery state of charge, air conditioning compressor status, and some indicator of fuel rate will be available for some vehicles, enhanced data will not likely be available for all vehicles instrumented in the study. The available budget, schedule requirements and type of datalogging system used will determine the level of enhanced PID data collection in the program.

ERG's review of fuel rates calculated using standard PIDs versus those calculated using injector fuel rate (an enhanced PID) suggests more investigation of the accuracy of fuel rates calculated using enhanced PIDs may be worthwhile. Although some differences in the rates appeared to be a result of different signal rise and fall rates during transients, other differences indicated some systematic bias may be present in the injector fuel rate data during certain operating modes. This could result in a bias in both instantaneous and average fuel rate results from the main study.

Conducting a study that extends over a year will capture seasonal variations in fuel economy and provide data that will yield insight into how various environmental factors affect fuel economy. Not performing a year-long study would largely eliminate the ability to assess the effects of potentially important seasonal temperature variation and seasonal trip behavior. A study that is conducted in a limited number of locations (a few regions and/or cities) may be more affordable than a true "nationwide" study where participants are far apart, in terms of managing datalogger installations, participant support, and ongoing study and data management. Datalogger costs could be substantially reduced if the main study were designed to be ongoing, instead of a one-time study. This would allow 20-50 vehicles to be instrumented and the dataloggers reused to gather additional data each year.

While it is feasible to expect that a large number of participants will be able to perform their own datalogger installations, some participants will likely require installation support of some type. Connector locations that result in a datalogger or its cabling being installed near brake or accelerator pedals or in locations where they can be bumped or snagged can be problematic from participant safety and data completeness standpoints.

Recommendations for Additional Work – Based on information learned during this study, ERG recommends additional analyses of some key issues prior to moving forward with a larger-scale study, as this additional recommended analysis could help provide information needed to reduce study costs and enhance data quality. Details of the items in the following list of recommended tasks are provided in the main body of the report.

- Develop method for estimating MAF from MAP to allow estimation[5] of FE for MAP-controlled fuel metering systems;
- Refine methods for calculating fuel rate for gasoline-powered vehicles equipped with narrow-band oxygen sensors;

[5] We acknowledge that a direct calculation of MAF from MAP values applicable to a wide variety of engine technologies does not appear to be possible. However, an analysis of existing data could provide a method to estimate MAF values from MAP values with relatively low error. Even so, the MAP-to-MAF conversion error would produce fuel economy estimates with larger errors in second-by-second and trip-average fuel economy values for MAP-based fuel metering systems than for MAF-based fuel metering systems. The size of the increased error may be acceptable.

- Develop methods for calculating fuel rate for diesel-powered vehicles;
- Determine the standard PIDs and non-standard PIDs[6] that are broadcast for a portion of representatives of the light-duty vehicle fleet, considering vehicle make, model, model year, engine and fuel type, and driver-selected drivetrain operating modes (e.g., sport, eco);
- Perform additional evaluation of accuracy of enhanced PID-based fuel rate estimates; and
- Collect and analyze additional OBD / dynamometer data from ongoing laboratory work from existing test programs.

[6] In particular, non-standard PIDs for air-conditioning compressor status, hybrid vehicle battery state of charge, and those that can be used to impute fuel rate.

1.0 Introduction

The International Council on Clean Transportation (ICCT) has asked Eastern Research Group (ERG) to conduct this pilot study to investigate the feasibility of collecting second-by-second data on a randomly selected set of light-duty OBDII-compliant in-use personal vehicles in the United States. The goal is to use the results of this pilot study to help develop a subsequent full-scale study. The focus of the full-scale nationwide data collection, which will be referred to as "the main study" in this report, would be to collect data that quantifies in-use fuel economy (FE), which is the distance driven per volume of fuel, and the major factors that influence in-use fuel economy.

The reader is invited to read this report as a thought exercise that covers most of the technical and logistic elements of a full-scale FE data collection study in the U.S. Even though at times the report may read as though decisions have already been made by ERG or ICCT, this report is in no way the final blueprint for the main study. The main purpose of this pilot study report is to illuminate some of the challenges of a fuel economy study and to suggest some possible solutions and approaches. With further thoughts and discussion among interested parties, cost-effective solutions may ultimately lead to a main study.

The results presented in this report are function of a set of assumptions and project objectives that have a direct impact on the specific design elements, such as sampling size, datalogging technologies, recruitment methods, and final costs. Those objectives would be discussed and adapted to specific requirements by the full-scale study funding entity or entities (i.e., consortium). We expect that modifying the objective would have an impact on methods and therefore total costs, but that most cost elements would remain intact.

Higher worldwide demand for gasoline and diesel fuels as a result of higher vehicle miles traveled, acknowledgment of finite fossil fuel resources, and political unrest in petroleum producing countries are some of the factors that have caused the price of motor fuels at the pump to increase. Additionally, every atom of carbon consumed by a motor vehicle produces one molecule of CO_2, a greenhouse gas. As a result of these financial and environmental pressures, the federal government, engine and vehicle manufacturers, and other organizations have been working to improve the fuel economy of future vehicles. The engine and vehicle manufacturers have responded to the growing need for improved fuel economy vehicles by making rapid changes to the technologies of the vehicles that they bring to the marketplace. The number of gasoline/electric hybrid vehicles in the fleet has increased rapidly over the last 10 years. The use of continuously variable transmissions and automatic transmissions with more than four gears, which allow engines to be operated closer to their maximum efficiencies, are more and more common in the fleet. Gasoline direct injection (GDI), in which gasoline is injected directly into the combustion chamber, has gone from virtually zero production levels in 2007 to roughly 1/4 of the U.S. production of 2013 of light-duty vehicles. Recently, Bosch celebrated the production of the 50-millionth GDI injector for the worldwide market.

The vehicle sample would be instrumented with dataloggers that collect OBDII information. The vehicles would be sampled from the national fleet (50 states plus District of Columbia) of 1996 and newer light-duty OBDII-compliant on-road vehicles with gross vehicle weights less than 8,501 pounds. Other on-road vehicles, such as OBDII-compliant Class 2b gasoline and diesel vehicles might be added to the study, depending on the desires of the main study's funding organizations. The study would not instrument motorcycles or vehicles that have electric plug-in capability.

Data from such a nationwide study could be used to answer a number of questions:

- What factors affect vehicle fuel economy and by how much?
- What driver behavior factors influence in-use fuel economy and by how much?
- How do weather and road grade affect fuel economy?
- How does driving behavior (speed, acceleration, trip length) vary by season, level of congestion, and region? Does driving behavior differ by technology type (e.g. diesel and hybrid vehicles)?
- What are the ranges and distributions of fuel economy influencing factors that U.S. vehicles are exposed to?
- How does in-use fuel economy deviate from the new vehicle fuel economy and environment label (FEEL) values?
- What are the estimated costs associated with recruiting vehicles, the datalogger, the cost of data transmission and other main cost sources?

Collecting this data would require a lengthy, extensive project, with many uncertainties about the sample size needed, the best way to recruit vehicles, the capabilities of dataloggers, and the best way to calculate fuel economy. Thus, ICCT funded a pilot study to address these uncertainties and facilitate design of a full-scale data collection program.

This report documents the results and findings of the ICCT fuel economy pilot study. The goal of this pilot study was to explore the feasibility and evaluate options and costs for the various methodologies and technologies that would be needed to collect in-use fuel economy data from passenger vehicles. The following four areas were investigated:

- Sampling: Describe options for defining the sample, including size and structure, of vehicles for the full-scale project.
- Recruiting: Identify a methodology and estimate the cost of recruiting passenger vehicles, installing dataloggers, and collecting data according to the sample size for the full scale project.
- Datalogger: Identify options for a data collection device and method for calculating in-use fuel economy, factors that affect fuel economy, and methods to record and/or transmit the information; also estimate the cost of alternative devices and measured methods, according to the sample size of the full scale project.
- Evaluate the accuracy of fuel economy calculations from dataloggers and assessing the cost of alternative methods to improve accuracy

Section 2 begins below with brief background discussions on the vehicle population under consideration for this fuel economy study and a background on fuel economy. The discussion of sample size and sample structure is included in Section 3. Alternative methods of defining the sample are provided. Section 4 provides a description of a vehicle recruitment methodology based on a selection of the options defined in Section 3. Section 5 describes the procedures that were used to evaluate different dataloggers. This section also includes a brief analysis of sample data from a top-ranked datalogger. Part of Section 5 also includes an analysis of data obtained from earlier light-duty vehicle datalogger projects to evaluate different methods of calculating fuel economy from OBDII information. Section 6 estimates the cost for a future full-scale private-vehicle fuel-economy study. The costs include estimates for vehicle sampling, recruitment, datalogger hardware, and the cost for data collection for a one year instrumentation period.

2.0 Background

2.1 Vehicle Population under Consideration

Table 2-1 shows the estimated number of registered light-duty vehicles in the United States at the end of the 2013 model year. The table shows counts for the vehicles under consideration in this pilot study, that is, 1996-2013 model year, light-duty OBDII-compliant vehicles that are not all-electric or plug-in hybrid vehicles and that are under 8,501 pounds GVWR. The second and third columns of the table show the estimated populations of gasoline and diesel light-duty vehicles from EPA's MOVES model. Those values were obtained from counts from MOVES 2010b for vehicles categorized as Passenger Cars and Passenger Trucks. The fourth, fifth, and sixth columns of the table show percentage estimates as provided by EPA's fuel economy report.[7] The italicized values in these columns for 2012 and 2013 model years were extrapolated by the authors. The percent of the fleet that is port fuel injection (PFI) is given in the seventh column and was calculated by difference. The values in the second and third columns of Table 2-1 (from MOVES) were used to calculate the populations by model year and vehicle propulsion system in the eighth through eleventh columns.

The light-duty fleet fractions for diesels and hybrids in Table 2-1 were compared with an analysis of 1Q2013 Colorado and 1Q2011 Maryland registration data. The diesel fractions for these two registration datasets were determined from the registration database fuel field and /or decodes of the database VINs and assignment to the light-duty category based on estimated GVWs of 8,500 pounds or less.[8] Figure 2-1 compares the Colorado and Maryland diesel fractions with the diesel fractions determined from the counts in the second and third columns of Table 2-1. The figure shows that the Colorado and Maryland diesel fractions generally fall above and below the MOVES estimates, and therefore tend to confirm the MOVES diesel fractions.

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[7] "Light-Duty Automotive Technology, Carbon Dioxide Emissions, and Fuel Economy Trends: 1975 Through 2011," Transportation and Climate Division, Office of Transportation and Air Quality, U.S. Environmental Protection Agency, EPA-420-R-12-001a, March 2012.

[8] Note that the method of designating vehicles as light-duty is different for the MOVES and for the state registration databases. These different bases mean that the fraction of vehicles determined from these three sources can be only approximately compared.

Table 2-1. Light-Duty Propulsion System Model Year Trends

Model Year	Registered Light-Duty Vehicles in SEP 2013[9]		Percent of Vehicles in the Light-Duty Fleet[10]				Registered Light-Duty Vehicles in SEP 2013				
	Gasoline	Diesel	Diesel[11]	Hybrid	GDI	PFI	Diesel	Hybrid	GDI	PFI	Total
1996	4,027,120	37,835	0.1	0.0	0.0	99.9	37,835	0	0	4,027,120	4,064,955
1997	4,833,550	41,469	0.1	0.0	0.0	99.9	41,469	0	0	4,833,550	4,875,019
1998	5,881,630	26,411	0.1	0.0	0.0	99.9	26,411	0	0	5,881,630	5,908,041
1999	7,440,710	74,526	0.1	0.0	0.0	99.9	74,526	0	0	7,440,710	7,515,236
2000	9,160,280	88,715	0.1	0.0	0.0	99.9	88,715	0	0	9,160,280	9,248,995
2001	10,236,490	78,812	0.1	0.0	0.0	99.9	78,812	0	0	10,236,490	10,315,302
2002	10,871,950	84,078	0.2	0.2	0.0	99.6	84,078	21,912	0	10,850,038	10,956,028
2003	11,191,940	89,164	0.2	0.3	0.0	99.5	89,164	33,843	0	11,158,097	11,281,104
2004	11,934,050	96,973	0.1	0.5	0.0	99.4	96,973	60,155	0	11,873,895	12,031,023
2005	12,555,020	101,508	0.3	1.1	0.0	98.6	101,508	139,222	0	12,415,798	12,656,528
2006	12,667,430	158,254	0.4	1.5	0.0	98.1	158,254	192,385	0	12,475,045	12,825,684
2007	12,719,070	159,777	0.1	2.2	0.0	97.7	159,777	283,335	0	12,435,735	12,878,847
2008	10,378,330	116,682	0.1	2.5	2.3	95.1	116,682	262,375	241,385	9,874,569	10,495,012
2009	9,031,740	97,030	0.5	2.3	4.2	93.0	97,030	209,962	383,408	8,438,370	9,128,770
2010	11,638,410	134,860	0.7	3.8	8.3	87.2	134,860	447,384	977,181	10,213,844	11,773,270
2011	13,142,060	150,039	0.6	4.0	13.7	81.7	150,039	531,684	1,821,018	10,789,359	13,292,099
2012	14,079,250	157,003	*1.0*	*4.3*	*17.7*	*77.0*	157,003	*612,159*	*2,519,817*	*10,947,274*	14,236,253
2013	14,929,080	165,053	*1.0*	*4.6*	*25.7*	*68.7*	165,053	*694,330*	*3,879,192*	*10,355,558*	15,094,133
						Totals:	1,858,187	3,488,746	9,822,002	173,407,362	188,576,297
						Fraction of 1996-2013 Light-Duty Fleet:	0.010	0.019	0.052	0.920	

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[9] MOVES 2010b.

[10] "Light-Duty Automotive Technology, Carbon Dioxide Emissions, and Fuel Economy Trends: 1975 Through 2011," Transportation and Climate Division, Office of Transportation and Air Quality, U.S. Environmental Protection Agency, EPA-420-R-12-001a, March 2012.

[11] The diesel percentages in this column were not used for the calculations. The values are shown just for completeness.

Figure 2-1. Comparison of Diesel Fractions of Light-Duty Fleets

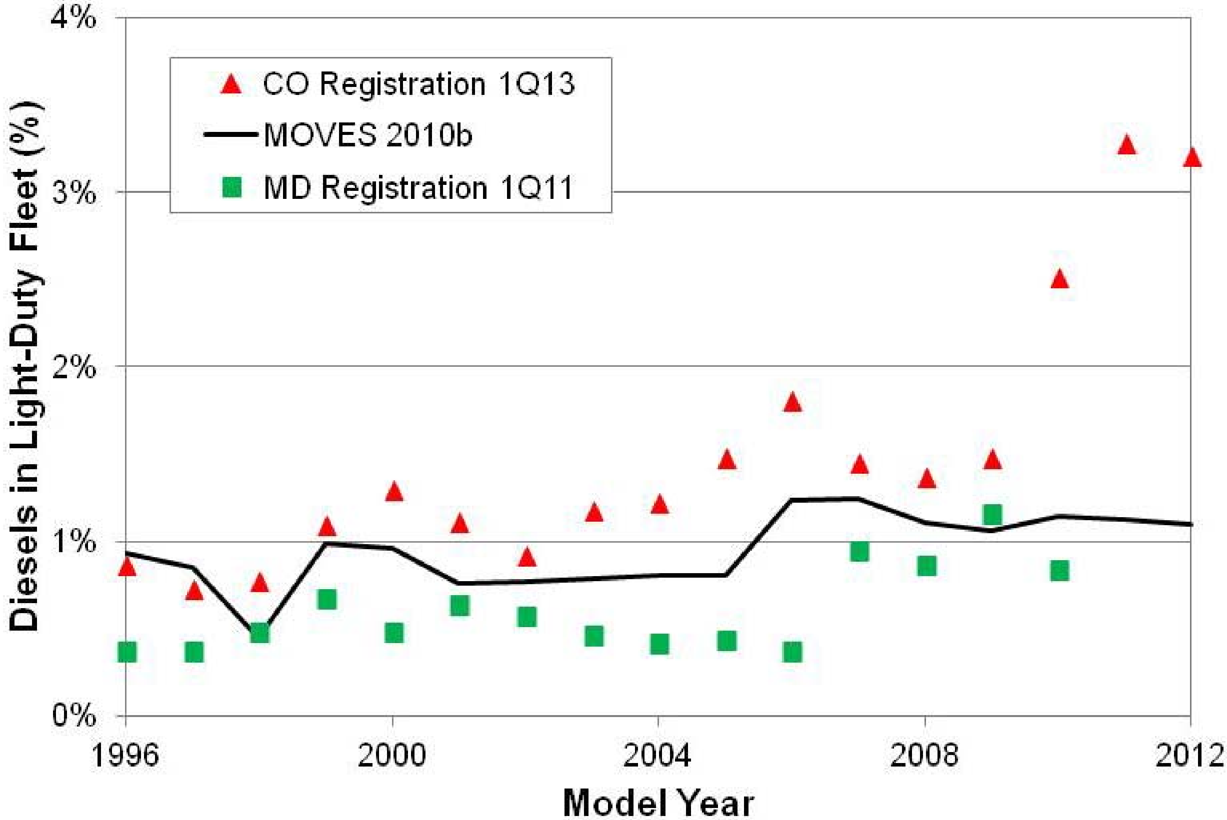
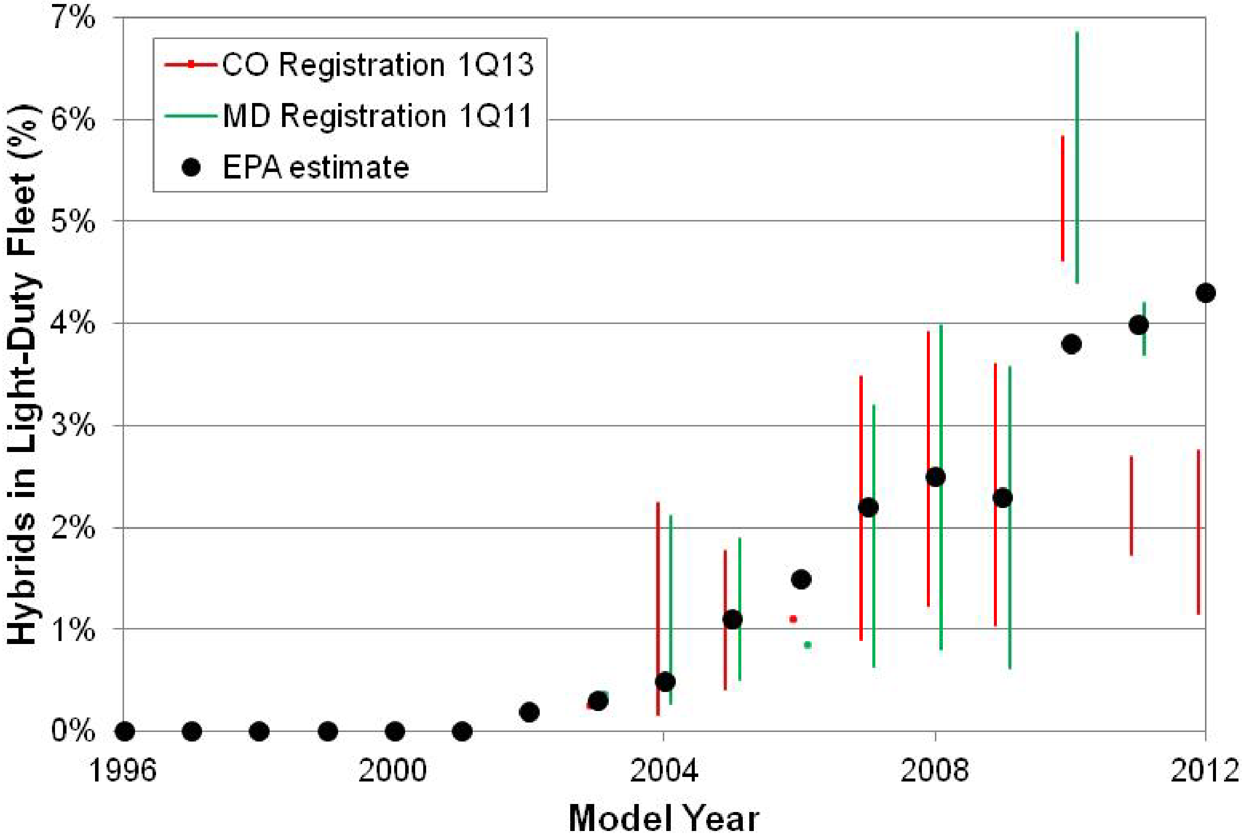


Figure 2-2 compares the hybrid fractions for the two registration databases with the hybrid fractions presented in the March 2012 EPA report.[12] In this instance the sources used to decode the VINs did not always reveal whether or not a vehicle was a hybrid. This behavior produced a range of possible hybrid fractions for each model year as designated by the green and red vertical colored bars in the figure. The lower end of the bar was derived from the vehicles whose VINs indicated that they were hybrids. The values for the upper end of the bars were derived from counts of all vehicles in series for which a hybrid powertrain was available as an option. Thus, the true value for the fraction of hybrids lies somewhere on each colored bar. The figure shows that in general the hybrid fraction trend as reported in the March 2012 EPA report passes through the error bars.

[12] "Light-Duty Automotive Technology, Carbon Dioxide Emissions, and Fuel Economy Trends: 1975 Through 2011," Transportation and Climate Division, Office of Transportation and Air Quality, U.S. Environmental Protection Agency, EPA-420-R-12-001a, March 2012.

Figure 2-2. Comparison of Hybrid Fractions of Light-Duty Fleets

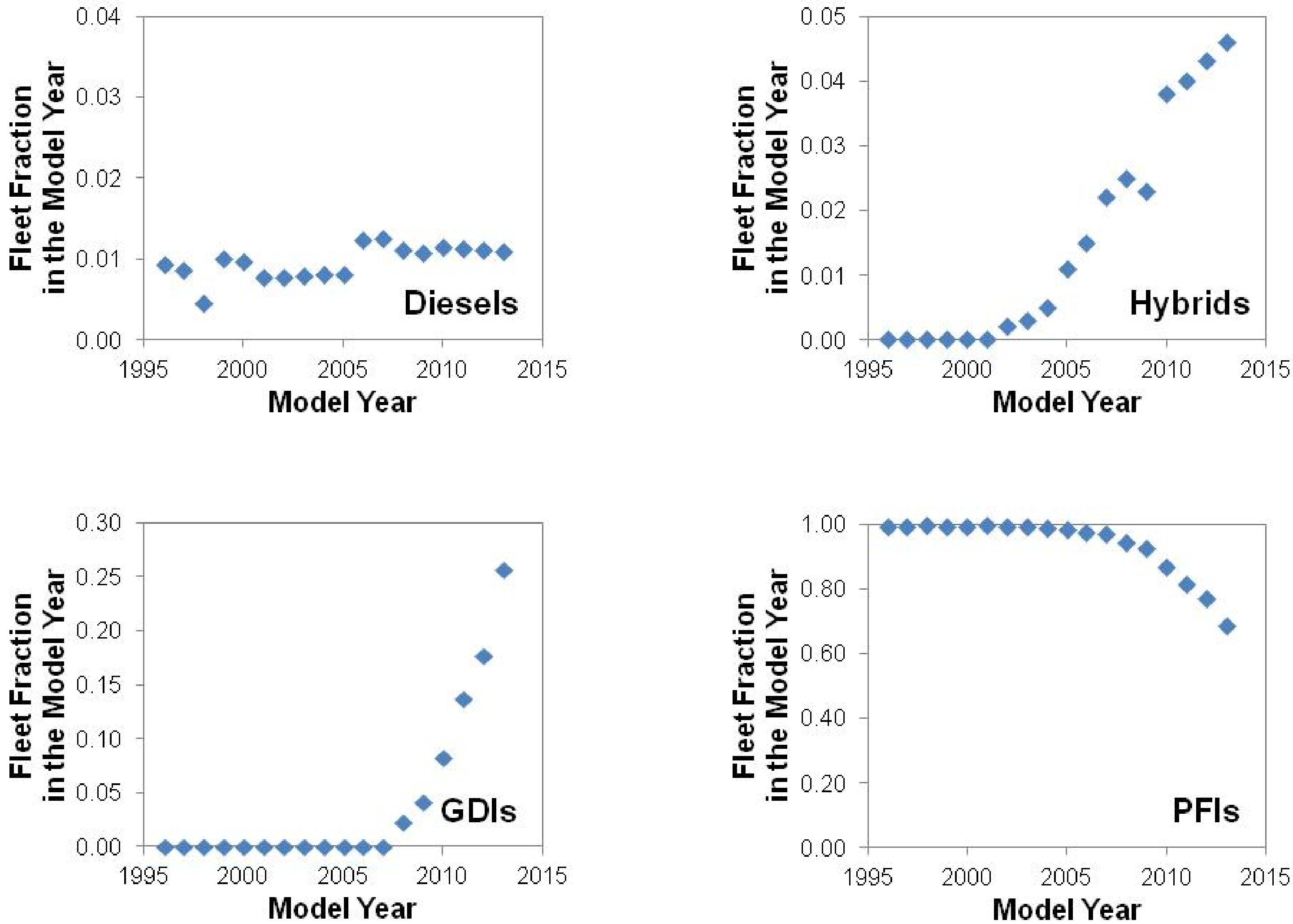


Based on the comparisons shown in Figures 2-1 and 2-2, we will use the values in Table 2-1 to estimate the diesel and hybrid fractions of the light-duty fleet.

This report discusses four propulsion systems: diesel, hybrid, gasoline direct injection (GDI), and port fuel injection (PFI). The values at the bottom of Table 2-1 indicate that in September 2013, the registered light-duty fleet is estimated from the values in this table to be almost 189,000,000 vehicles with an estimated 1.0% diesel, 1.9% hybrid, 5.2% GDI, and 92% PFI.

To examine the model year trends of propulsion system, the eighth through eleventh columns were converted to percentages and plotted in Figure 2-3. The diesel plot shows that the fraction of diesels produced over the last decade has been relatively constant at 1% of the fleet. The plot for hybrids shows that essentially no hybrids were produced before about 2002. Hybrid production has been increasing rapidly since that time and in 2013 gasoline hybrids make up

Figure 2-3. Light-Duty Propulsion System Model Year Trends



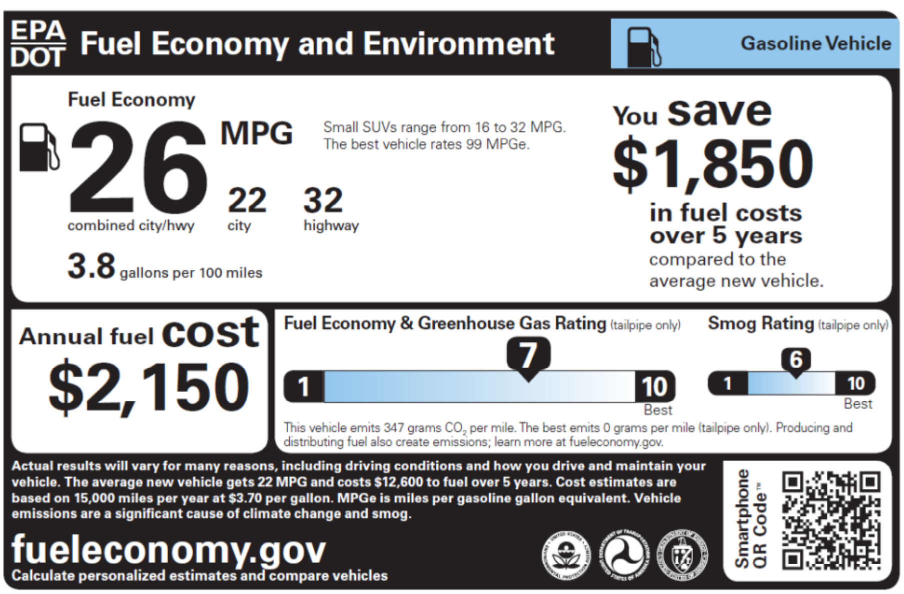
approximately 4% of the light-duty vehicle production. The GDI plot shows an even more rapid introduction of this technology into the marketplace than hybrids. The plot indicates essentially no GDIs were produced before 2008 but approximately 25% of the 2013 production will be gasoline direct injection vehicles. If this trend in GDI continues, the light-duty fleet will be dominated by GDI vehicles in just a few years. The PFI plot shows that this technology has dominated the market from 1996 through about 2005 at approximately 98%. Since then, as hybrid and GDI production has increased, the relative production of PFIs has dropped substantially.

Class 2b on-road gasoline and diesel vehicles could also be considered for inclusion in the main study. These vehicles may be used for personal transportation or for business purposes. In addition, only a portion of these vehicles are OBDII compliant.

2.2 Measures of Overall Fuel Economy

One measure of fuel economy is provided for new vehicles by the Fuel Economy and Environment Label (FEEL) that is placed on new cars that are for sale. An example of an FEEL is shown Figure 2-4 for a gasoline vehicle. The upper left hand corner of the label shows three values that give the vehicle shopper an indication of the fuel economy tendency of the vehicle: the FEEL City MPG, the FEEL Highway MPG, and the FEEL Combined MPG. For the label in the figure, these are 22, 32, and 26 miles per gallon (mpg).

Figure 2-4. Example Fuel Economy and Environment Label



The procedures used to determine the FEEL values for City MPG, Highway MPG, and Combined MPG are documented elsewhere. Briefly, the procedures involve testing a vehicle on a chassis dynamometer using standard driving cycles. The fuel economy results from those chassis dynamometer tests are weighted in various ways to produce the three MPG values on the FEEL label. These procedures test all vehicles under a consistent set of conditions. While those test conditions tend to produce FEEL values that are typical of average fuel economies that a vehicle may produce in typical use, the test conditions themselves cover a relatively narrow range in comparison with the range of conditions that the vehicle may experience during its service life.

The FEEL values for different combinations of model year, make, model, and engine are available as Excel spreadsheet that can be downloaded from www.fueleconomy.gov. The plots in Figure 2-5 show a brief examination of FEEL values for the 1996-2013 light-duty vehicles in that spreadsheet. Each plot is for one of the four propulsion systems that will be the focus of the main study. Each point in these plots represents one combination of model year, make, model, and engine. These plots are not an indication of the number of vehicles on the road or the number of vehicles that were produced for these different propulsion system technologies.

Figure 2-5 plots the tabulated values of the FEEL City MPG divided by the FEEL Highway MPG vs. the FEEL Highway MPG value for the four different propulsion systems. The FEEL Highway value is an indication of the fuel economy tendency of the vehicle primarily under high speed cruising conditions when accelerations are moderately low and speeds are relatively constant and high. These values are generally a measure of the fuel economy of the vehicle under relatively high efficiency conditions. The plots show that for 1996-2013 vehicles, the FEEL Highway values of PFIs vehicles range from about 12 to 40 mpg, the GDI vehicles range from about 16 to 40 mpg, the diesel vehicles range from about 16 to 44 mpg, and the gasoline hybrid vehicles range from approximately 16 to 60 mpg.

The vertical axis is the ratio of the FEEL City MPG divided by the FEEL Highway MPG. The FEEL City value is intended to reflect the fuel economy that a vehicle may obtain in urban driving – driving with more accelerations and decelerations and generally lower speed than during highway driving. The ratio of FEEL City to FEEL Highway is an indication of the amount of fuel economy debits that are produced when moving from highway to city driving. If there were no city debits relative to highway driving, then the ratio of FEEL City to FEEL Highway would be 1, which is shown in each plot by a horizontal dashed line. The plots show a ratio of about 0.5 to 0.95 for PFI vehicles, about 0.55 to 0.85 for GDI vehicles, about 0.65 to 0.85 for diesel vehicles, and about 0.7 to 1.15 for gasoline hybrid vehicles.

Among the four propulsion technologies, the plot in Figure 2-5 for hybrids is perhaps most different from the plots for the other three technologies. The most noticeable difference is that the FEEL City/Highway ratio for hybrids can exceed 1. This occurs for certain combinations of model year, make, model, and engine. Many other hybrids have FEEL City/Highway ratios substantially below 1; however, none are much lower than 0.7. The scatter of FEEL City/Highway ratios shows that just because a vehicle is a hybrid does not mean that its FEEL City value will be greater than its FEEL Highway value. Thus, a hybrid vehicle's relative city and highway fuel economies depend on the hybrid technology design.

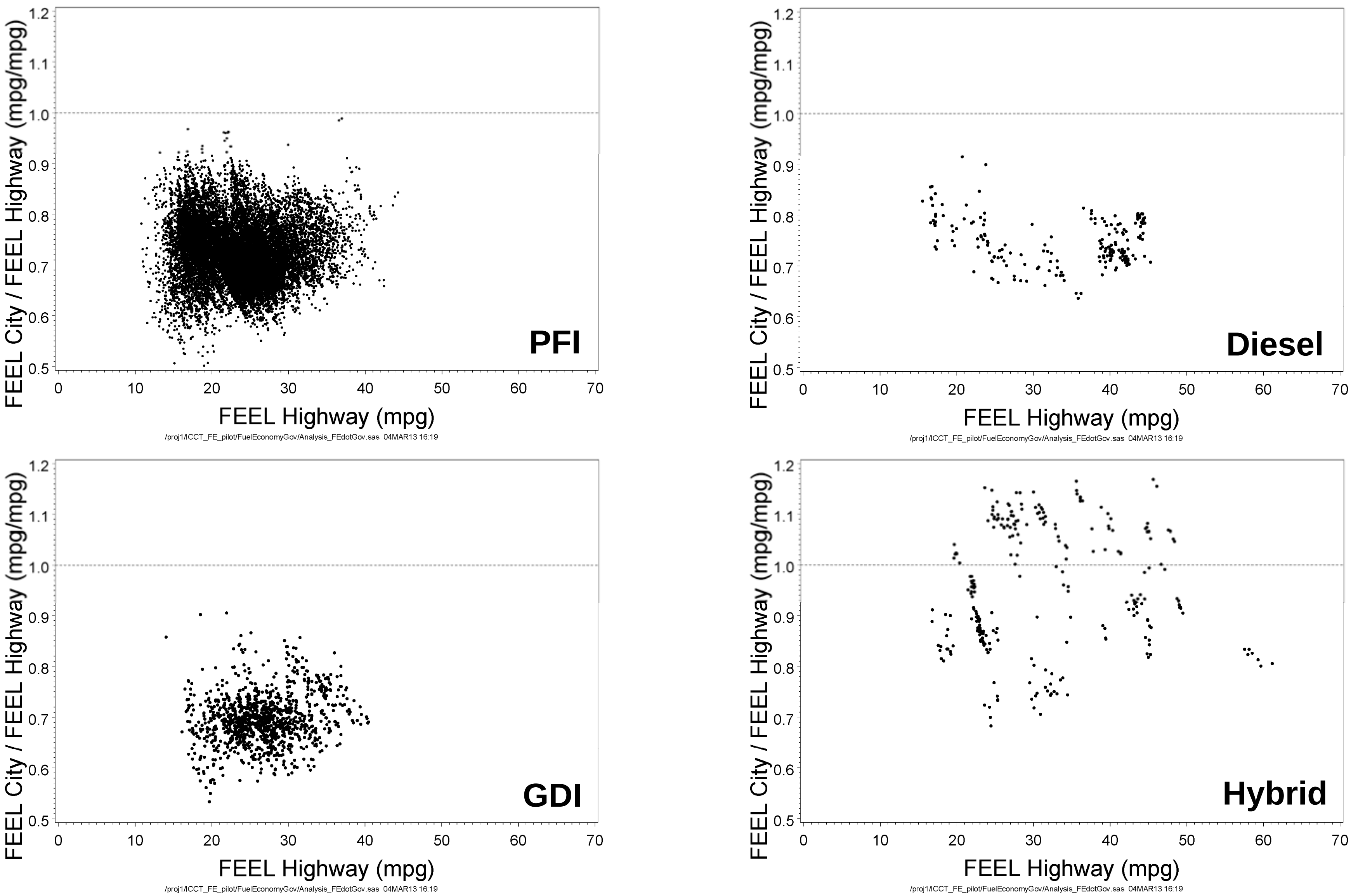
The range of FEEL Highway values for hybrids indicates that hybrids can have highway fuel economies that are just as low as the lowest FEEL Highway values for GDIs and diesels and almost as low as the lowest FEEL Highway values for PFIs. The highest FEEL highway values for hybrids are substantially higher than the FEEL Highway values for all of the other three propulsion technologies. Therefore, although hybrids can have high FEEL Highway ratings, all hybrids do not have them.

The examination of the plots in Figure 2-5 indicates that different vehicle and drivetrain designs have different fuel economy performance even within the same propulsion system. This is a consequence of the choices that manufacturers make when they design the vehicle. Because of different engineering designs and even within each type of propulsion system, individual vehicles to be instrumented in the main study should be selected to cover a wide range of FEEL Highway values and a wide range of FEEL City/Highway ratios so that the influences of different driver behaviors, driving conditions, and environmental factors can be generalized in any future analysis of the dataset to be produced by the main study.

2.3 Measures of Near-Instantaneous Fuel Economy

The fuel economies that a vehicle owner experiences can differ from the values that are printed on the FEEL. In fact, the FEEL itself states that "actual results will vary" as shown at the bottom of the example in Figure 2-4. The cause of deviations and the size of the deviations from the FEEL values is one of the questions that could be answered from an analysis of the main study's dataset.

Figure 2-5. FEEL City and Highway Values for 1996-2013 Light-Duty Vehicles



In addition to differences in the average fuel economies that an owner will see, second-by-second differences will be present. Owners will see these differences if their vehicle is equipped with an in-dash fuel economy display. The second-by-second fuel economy measurements on the vehicles instrumented in the main study would also capture these deviations. An analysis of the second-by-second fluctuations in fuel economy as a function of the second-by-second fluctuations in variables that affect fuel economy would be one of the main products of an analysis of the main study dataset.

To get an advance view of second-by-second fuel economy data, Figure 2-6 shows the distribution of one-second fuel economy values from one vehicle in EPA's Kansas City study[13]. The fuel economy values were determined from measurements of exhaust concentrations and flow rate using a portable emissions measurement system (PEMS) that was installed on the vehicle while the vehicle was driven in normal use. The vehicle was a 2003 Ford F150 pickup truck with a 4.6 liter port fuel injection engine. The FEEL values, which were obtained from fueleconomy.gov, for this vehicle are City: 14 mpg, Highway: 19 mpg, and Combined: 16 mpg. Data were available for only 2,684 seconds of operation. The average fuel economy observed during this period was 16.3 mpg, which is quite close to the FEEL Combined value of 16 mpg.

Figure 2-6 shows a tri-modal distribution of one-second fuel economy values. The lowest mode is at 0 mpg. The plot was made so that all observations in this mode had fuel economy values of exactly 0 mpg. These observations represent operation of when the vehicle is not moving at all such as when the vehicle is idling in a driveway or at a stoplight. The middle mode has FE values from just above 0 to about 37 mpg. This mode is likely to include vehicle operation during steady cruising, acceleration, or going up grades. Note that the location of the FEEL city, highway, and combined values are in the middle mode. The third mode has instantaneous FE values greater than 37 mpg. Operation during this mode will likely be when the vehicle is decelerating, going down grades, or when the driver's foot has decreased the throttle position.

[13] S. Kishan, A.D. Burnette, S.W. Fincher, M.A. Sabisch, W. Crews, R. Snow, M. Zmud, R. Santos, S. Bricka, E. Fujita, D. Campbell, P. Arnott, "Kansas City PM Characterization Study, Final Report," prepared for U.S. Environmental Protection Agency, prepared by Eastern Research Group, BKI, NuStats, Desert Research Institute, October 27, 2006, http://www.epa.gov/oms/emission-factors-research/420r08009.pdf.

Figure 2-6. Sample Fuel Economy Measurements for an In-Use 2003 Ford F150 4.6L PFI

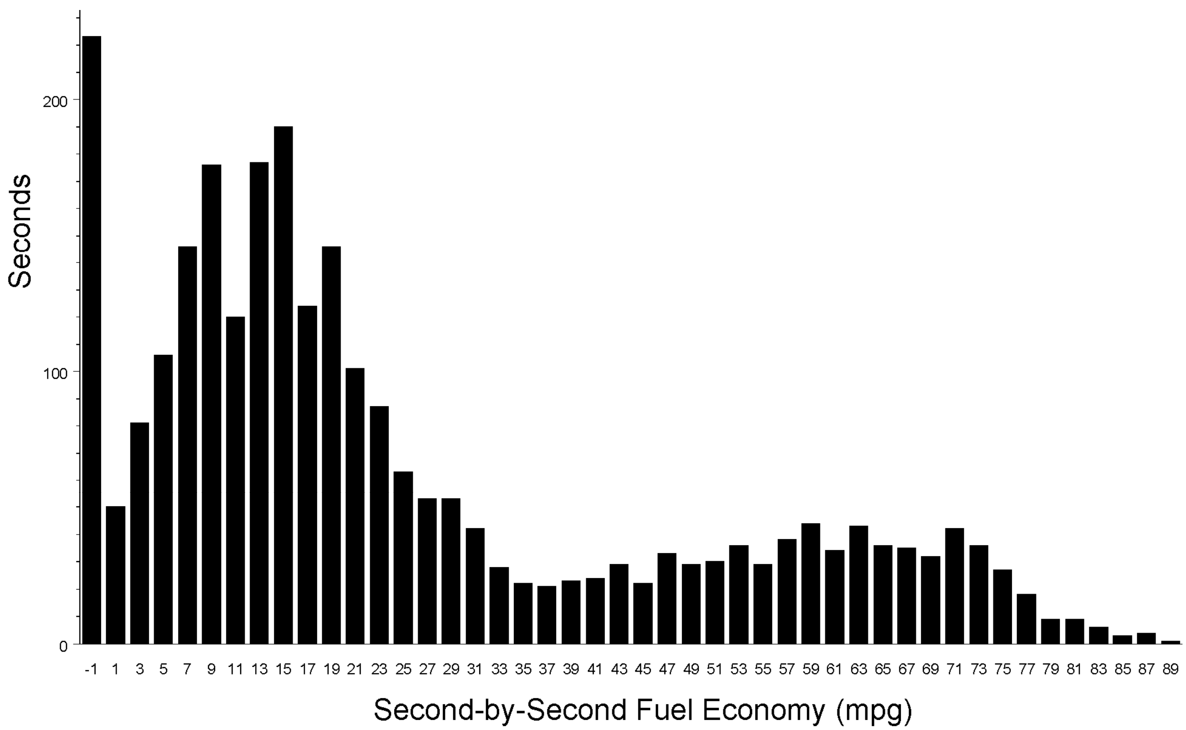


Figure 2-6 demonstrates that the observed second-by-second fuel economies for an in-use vehicle deviate substantially from the FEEL values. It can be expected that most non-hybrid vehicles will have second-by-second fuel economy distributions that look similar to Figure 2-6, that is a tri-model distribution. Differences in driving behavior, road conditions, vehicle environment, and vehicle drivetrain design will likely produce shifts in the distributions of the three modes. The factors that cause those shifts will be one of the questions to be answered in an analysis of the main study's dataset.

2.4 Mathematical Properties of Fuel Economy Values

Fuel economy is calculated as the ratio of the distance traveled to the volume of fuel used or as the ratio of the vehicle speed to the fuel rate. Because the fuel economy is a ratio, it has special mathematical properties that can be important during data analysis and, therefore, can be important during the planning of the data collection.

Let us consider the fuel economy for the discussions here as the ratio of the vehicle speed to the fuel rate. The speed of the vehicle has values from 0 to approximately 80 miles per hour. The fuel rate has values that range from just above 0 mL/s, which occur when the vehicle is idling, up to the maximum fuel rate for the engine. For engines that shut fuel off during decelerations or for some hybrids when the vehicle is not moving, the fuel rate will be 0 mL/s. The ratio of the vehicle speed to the fuel rate therefore, will have values from 0 mpg to infinity or at least to very large values.

It may be preferable to think about the analysis of fuel economy values in terms of the ratio of two analyses. The first analysis would be for the numerator, where the factors that influence vehicle speed would be considered, and a second analysis would be for the denominator, where the factors that influence fuel rate would be considered. By separating the analysis of fuel economy into these two separate analyses, any aberrations caused by fuel economy values that approach infinity would be avoided.

2.5 Factors that Influence Fuel Economy

Many factors can be expected to have influences on the fuel economy of a vehicle. Some factors could have large influences and, therefore, would be important to vary in the main study. Other factors could have minor influences on fuel economy and might not be cost-effective to investigate. As part of the first activity in designing the sampling plan and considering what variables to measure using the datalogger or other techniques, we have created Table 2-2 of factors with their estimated influences on fuel economy. It should be noted that the estimated effects on fuel economy were not usually a result of any data or literature search but were based on engineering judgment.

The first column of the table lists factors that potentially influence the second-by-second fuel economy. Several of these factors are related to each other. For example, driver aggressiveness and acceleration would be related to each other. Nevertheless, both are included in the table in the event that one is more convenient to measure than the other. The second, third, and fourth columns of the table list low, medium, and high values for the factor under consideration. The fifth, sixth, and seventh columns are estimates of the effect of those values on fuel economy that result from changes in the factor. For example, the first row in the table indicates that a moderately large acceleration of 7 mph/s might produce a decrease in fuel economy of about 80% relative to a steady cruise at 0 mph/s. On the other hand, a deceleration of -10 mph/s might cause the fuel economy to go three times higher than the fuel economy under steady-state cruise conditions.

Table 2-2. Factors that Influence Fuel Economy

FE-Influencing Factor	Range of Factor			Estimated Effect on FE (%)		
	Low	Mid	High	Low	Mid	High
Acceleration	7 mph/s	0 mph/s	-10 mph/s	-80%	0%	300%
Engine torque, inst.	140 N-m	30 N-m	0 N-m	-90%	0%	50%
Engine MAF	10,000 L/min	1,000 L/min	0 L/min	-90%	0%	100%
Engine MAP	100 kPa	40 kPa	30 kPa	-90%	0%	100%
Throttle position	WOT	steady-state	0%	-80%	0%	500%
Road grade	3%	0%	-3%	-50%	0%	200%
FEEL Composite MPG	low	medium	high	-50%	0%	50%
FEEL City MPG	low	medium	high	-50%	0%	50%
FEEL Highway MPG	low	medium	high	-50%	0%	50%
Speed	10 mph	45 mph	70 mph	-80%	0%	-50%
Vehicle weight, curb	4500#	3200#	2200#	-40%	0%	40%
Transmission gear	First	Fourth	n/a	-70%	0%	n/a
Propulsion System	PFI	Diesel, GDI	Hybrid	0%	10%	20%
Total accumulated miles	200,000 miles	100,000 miles	30,000 miles	-25%	0%	5%
A/C compressor status	On	n/a	Off	-20%	n/a	0%
Engine warm-up status	12 hour soak	warmed-up	n/a	20%	0%	n/a
Driver aggressiveness	jumpy	calm	n/a	-10%	0%	n/a
Altitude, inst.	5000 ft	1000 ft	0 ft	-15%	-2%	0%
Engine RPM within a gear	800 rpm	1200 rpm	3000 rpm	-10%	0%	-10%
Vehicle age	16 years	6 years	2 years	-25%	0%	5%
Car/Truck	truck	car	n/a	-10%	0%	n/s
Cargo weight	0 lb	1000lb	n/a	0%	-10%	n/a
Wind	20 mph head	0 mph	20 mph tail	-4%	0%	4%
Driver age	>75 yo	25yo -75yo	<25 yo	-15%	0%	3%
Socio-economics	<40k$	40k$ - 250k$	>250k$	-10%	0%	0%
Tire inflation pressure	15 psi	30 psi	40 psi	-5%	-2%	0%
New-vehicle break-in	odo<500 mi	odo>500 mi	n/a	-5%	0%	n/a
Fuel ethanol content	10% EtOH	0% EtOH	n/a	-3.4%	0%	n/a
Throttle jitter	none	pulsing	n/a	0%	3%	n/a
Road dry/wet/ice/snow	snow	wet	dry	-3%	-1%	0%
Aerodynamics, inst.	roof/trailer	smooth	n/a	-3%	0%	n/a
Ambient Temperature, inst.	105 F	70 F	30 F	-2%	0%	2%
Alternator load	60 A	20 A	0 A	-2%	-1%	0%
Tire age	<3 months old	>2 years old	n/a	-1%	0%	n/a
Driver gender	Male	Female	n/a	0%	0%	n/a
Transmission type	Manual	Automatic	n/a	0%	0%	n/a
Make	many	many	many	0%	0%	0%
Model	many	many	many	0%	0%	0%
Manufacturer	many	many	many	0%	0%	0%
Annual miles driven	<3000	3000-25000	>25000	0%	0%	0%

The factors are listed in Table 2-2 in the approximate order of their anticipated influence on fuel economy. So, for example, acceleration is expected to have the largest influence on fuel economy and it is listed at the top of the table. On the other hand, transmission type, that is, whether the transmission is a manual or an automatic transmission, was judged to have a small effect on fuel economy and, therefore, it is listed near the bottom of the table. It should be clear to the reader that the position of a factor in the ranking is influenced not only by the engineering judgment to estimate the size of the effect on fuel economy but also by the values that were considered for the low, medium, and high values in the range of factors. The idea of the ranking is to think about the different factors that could affect fuel economy and to at least approximately rank them. The ranking helps distinguish FE-dominant factors from FE-neutral factors so that when designing the vehicle sample or when selecting measured variables the most influential or most important variables are considered.

Note that of all the variables listed in Table 2-2 as having an influence on fuel economy, only throttle position and about seven other vehicle and engine variables (all are italicized) are varied during the determination of the FEEL values for a given vehicle so that the tested vehicle can follow the required driving cycle trace on the chassis dynamometer. All of the other variables (except the ten variables that are specific to the vehicle design and are in bold font) are varied during customer use but are not varied during dynamometer testing for the FEEL.

3.0 Sample Size and Structure Definition

The first task of the ICCT Pilot Study is to develop alternative sampling plans for selecting vehicles from the U.S. fleet for the main study to be instrumented with OBDII dataloggers with the goal of measuring instantaneous fuel economy. The vehicle sample would be taken from the national fleet (50 states plus District of Columbia) of 1996 and newer light-duty OBDII-compliant on-road vehicles. Note that for diesels, only 1998 and newer vehicles are OBDII compliant. In addition, only a portion of 1996 and newer Class 2b vehicles are OBDII compliant.

The data obtained from the instrumentation of the sample vehicles during the main study needs to be obtained such that analysis of that data would be able to describe fuel economy trends that are representative or typical of a variety of different vehicle technologies for typical behavior and operating environments of vehicles in the U.S. fleet.

The simplest approach for selecting a vehicle sample that would meet the objective would be to create a pure random sample. The problem with a pure random sample is that it is inefficient. This is a major problem since the cost of selecting and instrumenting a single vehicle will be high, and for a pure random sample a large number of vehicles would need to be instrumented to ensure that a sufficient number of the more unusual technologies and more unusual vehicle operating environments would be in the sample. A more efficient approach is to use a stratified, random sample. To achieve the objective with a stratified, random sample, we have addressed three separate notions for the main study:

1. Stratification – Create a sample of vehicles from the U.S. fleet based on a few (less than or equal to three) attributes of vehicle technology that are closely associated with overall fuel economy tendency. The attributes should be easily obtainable, quantitative, and specific to the individual vehicles under consideration for the sample. For this activity, using attributes that are closely related to fuel economy tendency is most important.

2. Representativeness – Next in importance, attempt to ensure that the sample as a whole will be likely to operate during second-by-second data collection in a range of environments, including driver behavior, roadway characteristics, cargo, and weather, that are typical of the range of environments across the U.S. We want the sample to be an unbiased reflection of the entire country and not unduly weighted towards, for example, urban vehicles or vehicles is specific regions of the country.

3. Analysis – Rapidly changing conditions, specifically the second-by-second quantities obtained by on-board dataloggers or even the ranges of these quantities, cannot be used to select vehicles for the sample or ensure representativeness

because those quantities cannot be known before the vehicles are selected and instrumented. However, once the second-by-second data has been obtained over a long period of time on sample vehicles, analyses will allow fuel economy to be determined as a function of second-by-second variables such as road grade, speed, acceleration, and ambient temperature.

The discussion begins in Section 3.1 with a consideration of the factors that influence instantaneous fuel economy because the variables that would be used to define the main study's stratification plan and fleet representation plan would be selected from those factors. Section 3.2 describes two options for a stratification plan. Section 3.3 describes two options for a U.S. fleet representation plan. Other plans could certainly be devised.

3.1 Consideration of Factors for Sample Creation

The list of factors in Table 2-2 can be considered for use in defining the vehicle sample and for other uses. The factors have been tentatively characterized by four descriptors as shown in Table 3-1. The assignments have been made based on a whether or not variables are functions of time, whether the variables could be objectively quantified for a particular vehicle or driver, whether the distribution of the variable for the U.S. fleet was known or could be easily determined, and the number of levels that a categorical variable might have.

Table 3-1 shows a division of the variables into Second-by-Second Data (Column 2) variables and Basic Data variables (Columns 3, 4, and 5).

Second-by-Second Data variables are variables that change rapidly with time and whose changes with time can be expected to affect instantaneous fuel economy or are needed to calculate instantaneous fuel economy. Second-by-Second Data variables are candidates for acquisition by the datalogger. Because Second-by-Second Data variables change rapidly with time and are not known before data is logged from vehicles in the sample, those variables cannot be used to select vehicles for the sample.

Basic Data variables are variables that characterize the vehicle, driver, or vehicle home location and are constant or change slowly with time. In, general, Basic Data variables would be recorded once and therefore do not need to be acquired by the datalogger. Basic Data variables can be further assigned to categories based on their desired use in creating the sample and representing the U.S. fleet.

Table 3-1. Candidate Factors for Sample Design and Data Collection

FE-Influencing Factor	Second-by-Second Candidates	Basic Data Variables		
		Stratification Candidates	U.S. Fleet Representation Candidates	Other Basic Data Candidates
Acceleration	X			
Engine torque, inst.	X			
Engine MAF	X			
Engine MAP	X			
Throttle position	X			
Road grade	X			
FEEL Composite MPG		S1		
FEEL Highway MPG		S2		
FEEL City/Highway ratio		S2		
Speed	X			
Vehicle weight, curb				O
Transmission gear	X			
Propulsion System		S1, S2		
Total accumulated miles			R	
A/C compressor status	X			
Engine warm-up status	X			
Driver aggressiveness	X			
Altitude of Home Location			R	
Altitude, inst.	X			
Engine RPM within a gear	X			
Vehicle age			R	
Car/Truck			R	
Cargo weight	X			
Wind	X			
Driver age			R	
Socio-economics			R	
Tire inflation pressure	X			
New-vehicle break-in				O
Fuel ethanol content	X			
Throttle jitter	X			
Precipitation, climatic			R	
Road dry/wet/ice/snow	X			
Aerodynamics, inst.	X			
Ambient Temperature, climatic			R	
Ambient Temperature, inst.	X			
Alternator load	X			
Tire age				O
Driver gender			R	
Transmission type			R	
Make				O
Model				O
Manufacturer			R	
Annual miles driven		S1		

The discussion below discusses each of the four characterizations of variables presented in Table 3-1. These characterizations are intended to begin the consideration of variables for creating a vehicle sample. Planning for the main study can certainly modify the characterizations suggested in this pilot study and specifically those shown in Table 3-1.

Second-by-Second Variable Candidates – The second column in Table 3-1 indicates the second-by-second variable candidates with an X. In general, these are variables that are time dependent and follow operation and the operating environment of the vehicle. Some variables describe vehicle operation, engine operation, roadway conditions, transmission operation, air-conditioning operation, weather that the vehicle experiences, changes in cargo weight and vehicle aerodynamics due to cargo, changes in fuel properties, and changes in tire properties. Most of these variables are functions of time in the normal operation of any vehicle. These include, for example, acceleration, transmission gear, A/C compressor status, cargo weight, wind, and aerodynamics. A few of these variables change slowly with time or are difficult to measure using a survey. These include driver aggressiveness, tire inflation pressure, and fuel ethanol content. Because second-by-second variables can vary rapidly with time and cannot be known for an individual vehicle before datalogger installation, these variables cannot be used to select vehicles for the sample. However, these variables are important candidates to consider for collection with the datalogger.

Stratification Candidates – The vehicles in the sample could be selected from the U.S. fleet in two different ways: 1) random selection, or 2) stratified, random selection. Random selection would tend to result in a vehicle sample that has characteristics of the most common vehicles in the fleet; the less common technologies, for example, would not likely be well represented in the sample. Relatively small samples, which may describe the main study's sample, can benefit from the stratified, random method in which the sample is enriched in vehicles with less common attributes. Such a sample could provide a sufficient number of vehicles for analysis of several technologies – whether or not those technologies are common in the fleet. We recommend the stratified, random approach for the main study. The question then becomes, "What Basic Data variables should be used for stratifying the sample?"

The stratification variables must be known for vehicle candidates early in the sample creation process because these factors would be used to select vehicles from the eligible vehicle pool for inclusion in the sample. Any of the Basic Data variables listed in Table 3-1 could be determined for an individual vehicle from information obtained from the vehicle owner. However, given that fuel economy is the main focus of the main study, sample stratification based on Basic Data variables that are more closely related to fuel economy is preferred.

For this pilot study we have considered two alternatives for sample stratification. Section 3.2.1 describes Stratification Plan 1, which would estimate U.S. fleet fuel consumption and CO_2 production with optimum precision. That plan uses propulsion system, FEEL composite MPG, and annual miles driven as the stratification variables, which are designated as S1 in the third column of Table 3-1. Section 3.2.2 describes Stratification Plan 2, which would provide a dataset that could be used to quantify the effects of major fuel-economy-influencing factors for a wide variety of technologies. That plan uses propulsion system, FEEL highway MPG, and FEEL city/highway ratio as the stratification variables, which are designated as S2 in the third column of Table 3-1. Other alternative stratification plans could certainly be designed for the main study.

The type of propulsion system and the FEEL values can be determined from the vehicle's VIN and information from fueleconomy.gov. The annual miles driven can be estimated from an initial interview with the vehicle owner.

Fleet Representation Candidates – Besides selecting vehicles for the sample according to stratification variables, having the sample, as a whole, represent the U.S. fleet's operating environment has advantages. In particular, if the sample proportionally represented the U.S. fleet in terms of fleet operating environment characteristics, then the second-by-second operating data obtained from the dataloggers would characterize the operating environment of the U.S. fleet – something that may not be currently known. Another benefit of proportional sampling with respect to fleet representation variables is that, as described below, it helps ensure that a sample that is highly skewed with respect to one of the fleet representation variables would not inadvertently occur.

Accordingly, another subset of Basic Data variables, which are independent of the stratification candidate variables, can be selected to define the characteristics of the U.S. fleet. For discussion purposes, we have selected the eleven variables designated in the fourth column of Table 3-1 by R. Their values can be determined early in the vehicle selection process for vehicle sample candidates using information provided by the owner including zip code, VIN, and driver demographics. Table 3-2 shows sources that can be used to estimate the values or distributions of the U.S. fleet.

In the usual application of the stratified, random technique, vehicles within each of the combinations of stratification variables would be selected randomly. However, because of statistical fluctuations always present during random sampling, just selecting vehicles randomly within each stratum will not ensure that the overall sample will have characteristics proportional to those of the U.S. fleet.[14] One possible approach is first to select vehicles randomly within each of the combinations of stratification variables and then to adjust the set of vehicles selected such that the values for the 11 representation variables of the sample matches those of the U.S. fleet. The adjustment would be made by dropping vehicles from the initial set and replacing them with vehicles from the eligible pool until the representative properties of the set matches the representative properties of the U.S. fleet. The resulting sample would therefore not be strictly a random sample, but its creation would have had an element of randomness.

Table 3-2. Information Sources for U.S. Representative Candidate Variables

Factor Type	Factor	Estimated U.S. Fleet Characteristics
Vehicle	Vehicle age	MOVES defaults
	Car/Truck	MOVES defaults
	Transmission type	Inspection/Maintenance data: Transmission Type
	Manufacturer	Registration data
Usage	Total accumulated miles	Inspection/Maintenance data
Driver	Driver age	2009 FHWA HHTS: Driver Age
	Socio-economics	2009 FHWA HHTS: Demographics
	Driver gender	2009 FHWA HHTS: Driver Gender
Geography	Altitude of Base Location	2010 Census: Zip → Altitude
	Precipitation, climatic	2010 Census: Zip → Precipitation Distribution
	Ambient Temperature, climatic	2010 Census: Zip → Temperature Distribution

Several of the 11 fleet representation candidate variables benefit from additional discussion. Total accumulated miles is a measure of the accumulated wear and tear on the vehicle. In general, we expect that fuel economy will eventually decrease as a vehicle accumulates a large amount of mileage, due to malfunctions and wear and tear. However, at the beginning of a vehicle's life, mileage accumulation will reduce friction in the engine, transmission, drivetrain, and tires, which will produce gradual improvements in fuel economy until malfunctions start to occur and the tires are replaced. The datalogger would record mileage accumulated during instrumentation, which would be used with owner interview information to determine total accumulated miles, annual miles driven, and new-vehicle break-in.

Because the fuel economy tendency for a given year, make, model, and engine combination would already be present in the FEEL MPG values, make and model are not being proposed for inclusion in the sampling design for fleet representation variables. On the other

[14] As an example of how statistical fluctuations can produce non-proportionate samples from a random process, consider flipping a coin. The probability of getting heads for a single flip is 0.5. The probability of getting 5 heads when the coin is flipped 10 times, which is the proportionate result, is only 0.246. Thus, a non-proportionate result will be obtained more than 75% of the time for this process.

hand, the vehicle manufacturer (e.g., GM, Ford, Chrysler, Japan, Europe categories) could be included in the sampling design simply to ensure sampling is appropriately distributed among manufacturers.

Whether a vehicle is a car or a truck can have an influence on fuel economy since, taken as groups, cars and trucks have different fuel economies. However, just as for make and model, the FEEL MPG values already contain the tendency of trucks and cars to have different fuel economies. Just as for vehicle manufacturer, Car/Truck could be included as a fleet representative variable simply to ensure that sampling is appropriately distributed among vehicle types.

Other Basic Data Candidates – The fifth column of Table 3-1 indicates with an O the variables that have been designated as Other Basic Data candidates. In general, Other Basic Data variables are Basic Data variables that have not been used to stratify the sample or to ensure that the sample is representative of the U.S. fleet. Nevertheless, the values of Other Basic Data variables are important to record because they are not generally recorded by the dataloggers installed on the instrumented vehicles. In the particular variable assignments envisioned by Table 3-1, the Other Basic Data variables benefit from some explanation.

Vehicle curb weight clearly has an effect on fuel economy. However, FEEL Composite value, which is designated for Stratification Plan 1, and FEEL Highway MPG and FEEL City/Highway ratio, which are designated for Stratification Plan 2, contain the influence of vehicle weight in their values. Therefore, the additional use of vehicle weight for those plans would be redundant. Similarly, the effects of vehicle make and model are also included in the FEEL values. In addition, their possible use as fleet representative candidates is not practical given the large number of makes and models in the U.S. fleet.

The new-vehicle break-in variable is one variable that would be determined by the second-by-second data by tracking odometer reading for newly manufactured vehicles in the sample.

Tire age is an example of a variable that has an influence on a vehicle's fuel economy but that would be difficult to use to stratify the sample or to ensure its fleet-representativeness. Given all of the many variables that are expected to have larger influences on fuel economy, tire age could be assigned to the Other Basic Data category. Nevertheless, owners of participating vehicles should be requested to provide receipts of any new tire purchases so that the effect of the new tires on fuel economy might be determined during data analysis.

3.2 Alternatives for Stratifying the Sample

To demonstrate approaches for creating a stratified sample, two alternatives for stratifying the vehicle sample are discussed below. The first alternative, discussed in Section 3.2.1, has the goal of selecting an optimally stratified sample that would obtain the minimum uncertainty in the volume of fuel used per U.S. light-duty vehicle per year. The second alternative, discussed in Section 3.2.2, has the goal of generating a dataset that could be used to determine the size of the influences of various factors on the fuel economies of vehicles that have a wide range of fuel economy tendencies.

3.2.1 Stratification Plan 1 – Measuring Total Fuel Consumption of the U.S. Light-Duty Fleet: Propulsion System, FEEL Composite, Annual Distance Driven

This first alternative for stratification of the vehicle sample focuses on creating a dataset that can be used to quantify the annual fuel consumption and CO_2 emissions of the national fleet with optimum precision. An estimate of the fleet's annual fuel consumption could be made from the FEEL Composite values of vehicles in the fleet; however, since the each vehicle's actual in-use fuel economy depends on the vehicle's operation and operating environment, a calculation based just on FEEL Composite values may be biased. A quantification of the influences of various factors on the fuel economies of a wide range of vehicle technologies and fuel economy tendencies could improve fleet estimates of fuel consumption and thereby CO_2 emissions.

Optimal stratified sampling can be used to determine the structure of an "efficient" sample set. In this case, the goal would be to minimize the uncertainty in an estimate of the mean fuel consumption for the average vehicle in the national fleet. The techniques for generating an optimized stratified sample are discussed in Appendix A. Using those techniques, we present Table 3-3, which demonstrates estimating the uncertainty in the fuel consumption of the average fleet vehicle for a given sample size. Because this calculation is a demonstration, we have used entirely artificial values in the calculation. The results that appear here should not be used for designing the actual sample for the full-scale project.

Table 3-3. Demonstration Calculations for Sample Structure Determination for Optimal Stratification

A	B	C	D	E	F	G	H	I	J	K	L	M	N
	Definition of Strata		Fraction of Fleet in Strata			Characteristics of Fleet Operation				Sample Structure Calcs		Population Calcs	
					W_h			**xbar**	**s_h**	**W_h*s_h**	**n_h**	**W_h*xbar**	**$(W_h*s_h)^2/n_h$**
Stratum A|B Number	Stratum A based on FEEL Composite (miles per gallon)	Stratum B based on Annual Miles Driven (thousands of miles)	Fraction of Population in Stratum A: FEEL Composite Group	Fraction of Population in Stratum B: Annual Miles Driven Group	Fraction of Population in Stratum A|B	Mean FEEL Composite MPG	Mean Annual Miles Driven	Mean Gallons per year	StdDev of Gallons per year (assume 50% of xbar)		Number of Sample Vehicles Allocated to each Stratum		
1	<15	<5	0.1	0.1	0.01	12	4000	333	167	2	0.5	3	6.1
2	<15	5 to 25	0.1	0.7	0.07	12	13000	1083	542	38	10.3	76	139.6
3	<15	>25	0.1	0.2	0.02	12	30000	2500	1250	25	6.8	50	92.0
4	15 to 25	<5	0.6	0.1	0.06	20	4000	200	100	6	1.6	12	22.1
5	15 to 25	5 to 25	0.6	0.7	0.42	20	13000	650	325	137	37.1	273	502.5
6	15 to 25	>25	0.6	0.2	0.12	20	30000	1500	750	90	24.4	180	331.3
7	25 to 35	<5	0.2	0.1	0.02	30	4000	133	67	1	0.4	3	4.9
8	25 to 35	5 to 25	0.2	0.7	0.14	30	13000	433	217	30	8.2	61	111.7
9	25 to 35	>25	0.2	0.2	0.04	30	30000	1000	500	20	5.4	40	73.6
10	>35	<5	0.1	0.1	0.01	40	4000	100	50	1	0.1	1	1.8
11	>35	5 to 25	0.1	0.7	0.07	40	13000	325	163	11	3.1	23	41.9
12	>35	>25	0.1	0.2	0.02	40	30000	750	375	8	2.0	15	27.6

Sample Size:	Population Mean Gallons per Year:	SD of Population Mean Gallons per Year:
100	736	37
		Coefficient of Variation: 5.00%

Select stratifying variables – The discussion surrounding Tables 2-2 and 3-1 focused on identifying candidate variables for the vehicle sample. In Table 3-1, five variables were designated as candidates for sample stratification. For a stratification design to minimize the uncertainty in the average light-duty fleet vehicle annual fuel consumption, the following variables, which were indicated with S1 in the third column of Table 3-1, can be chosen:

- Propulsion System – This categorical variable has values of PFI, GDI, hybrid, and diesel. It should be used as a stratification variable because different propulsion systems can respond differently to fuel economy factors.

- FEEL Composite value – This variable may be the current best single value that estimates average fuel economy. It can be looked up in fueleconomy.gov based on model year, make, model, and engine.

- Annual Miles Driven – The value of this value can be estimated by the vehicle owner. The FEEL Composite MPG multiplied by the Annual Miles Driven provides an estimate of the volume of fuel used by a vehicle that is a candidate for the vehicle sample.

The U.S. fleet's proportions of the three stratification variables need to be determined to guide the stratification. As shown in Table 3-4, the FEEL Composite values of vehicles in the national fleet can be obtained by matching vehicle model year, make, and model for several sets of state registration data with composite values reported in fueleconomy.gov. The distribution of annual miles driven for the U.S. fleet cannot be obtained from MOVES. MOVES contains only the average annual miles driven as a function of vehicle age. However, an analysis of odometer readings from I/M programs can provide an estimate of the distribution of annual miles driven.

Table 3-4. Information Sources for the Vehicle Sample for Stratification 1

Factor	Sources of Information for:	
	Sample Stratification/De-Stratification	**Sample Vehicle Selection**
Propulsion System	Registration data + VIN	Survey: VIN
FEEL Composite MPG	Registration data + fueleconomy.gov	Survey info + fueleconomy.gov
Annual miles driven	Inspection/Maintenance data	Survey: MilesDriven

A separate stratification design would be desired for each of the Propulsion Systems. As shown in Table 3-4, Propulsion System can be determined on a sample of registration data from several states to determine the fraction of propulsion systems that are present in the U.S. fleet. However, based on the low fractions of non-PFI vehicles in the 2013 calendar year fleet as estimated in Section 2.1, it may be necessary to target almost all of the willing-to-participate drivers of diesel, gasoline direct injection, and hybrids for instrumentation in order to instrument a sufficient number of those technologies regardless of FEEL Composite value or annual miles driven. Thus, the demonstration calculation presented below is intended to be a simulated calculation for the only PFI vehicles.

Table 3-3 shows how a stratified sample that minimizes the uncertainty in annual fuel consumption could be designed for PFI vehicles. Columns B and C show the two types of strata that could be used to define 12 strata for the sample set. Column B shows Stratum A which is based on the FEEL Composite value of a vehicle. These values can be obtained from www.fueleconomy.gov. Column C shows the Stratum B values of annual miles driven as obtained from the survey of vehicle owners. Together, Stratum A and Stratum B create 12 different strata for the PFI vehicles as shown by the 12 identifiers in Column A. Column D shows the (artificial[15]) fraction of the population in the different MPG groups. Column E shows the (artificial[16]) fraction of the population in the three different annual-miles-driven groups. Column F, which is produced by the product of Column D and Column E, gives an estimate of the (artificial) fraction of the population in all 12 strata. The values in Column F sum to one. Column G gives the (artificial[17]) average FEEL Composite values for each of the 12 strata. Column H gives the (artificial[18]) average annual miles driven for each of the Stratum B values. Column I, which is the (artificial[19]) average gallons per year used by vehicles in each of the 12 strata, is calculated in Table 3-3 by dividing Column H by Column G. Column J is the (artificial[20]) standard deviation of the mean values in Column I. For this demonstration, we have simply assumed that the standard deviations are 50% of the means in Column I.

There are at least two contributions to the standard deviations in Column J. The first contribution is the variability among the FEEL Composite values of vehicles of different descriptions (year, make, model, engine) that are in the same A|B stratum. The other contribution to the standard deviations is the variability of the actual fuel economy among vehicles of the same description (year, make, model, engine) and in the same A|B stratum as a consequence of

[15] Better values for these entries could be determined by application of the fueleconomy.gov values to a registration dataset.
[16] Better estimates of these values could be obtained from a careful analysis of inspection/maintenance odometer data.
[17] More accurate values for this column could be obtained using fueleconomy.gov and state registration datasets.
[18] More accurate values for these annual miles driven values could be obtained for real vehicles by considering an inspection/maintenance dataset. Because very few of the very newest vehicles participate in inspection/maintenance programs, the mean annual miles driven for the newest vehicles would have to be estimated.
[19] More accurate values could be obtained by dividing the annual miles driven for individual vehicles in an I/M dataset by their FEEL Composite values and then taking the mean.
[20] These standard deviations could be estimated more accurately by propagating the errors within each of the 12 strata for Column G with the errors for each of the 12 strata in Column H. Even better values could be obtained using the variabilities in the annual fuel consumption estimated for vehicles in an inspection/maintenance dataset.

different vehicle operation caused by differences in operating environment and driving characteristics. Fueleconomy.gov can be used to determine the variability among vehicles of different descriptions to arrive at an estimate of the first variability contribution. Fueleconomy.gov also has self-reported average fuel economies by drivers of vehicles. However, while these variabilities could be used to estimate the second portion, we suspect that these variabilities are much narrower than the true distribution of average fuel economies. This is a consequence of the likelihood that drivers of vehicles are more likely to self-report high fuel economies over low fuel economies because of pride. Fueleconomy.gov self-reported fuel economies can be used to estimate the dependence of the variability of average reported fuel economies on the composite fuel economy values. Then, based on those trends, the variability of average reported fuel economies may need to be inflated to correct for self-reporting bias.

Columns K and L show the results of the sample structure calculations for a desired sample size of 100 vehicles and follow the equations given in Appendix A. Of particular interest are the results shown in Column L which gives the number of vehicles in each of the 12 strata to produce a minimum in the uncertainty of the fuel consumption of the average vehicle in the fleet. There are basically two contributions to the number of vehicles shown for each stratum in Column L. If the fraction of the fleet for a given stratum is small (Column F), then the tendency is for the number of vehicles in the sample to be small since a small fraction of the fleet would not have a large influence on the overall amount of fuel consumed by the fleet. The second contribution is the variability of the amount of fuel used in each stratum. This is given in Column J and is related to the average fuel economy and average annual miles driven in each stratum. Because of these relationships, more vehicles are allocated to strata that represent larger fleet fractions, vehicles with lower fuel economies, and vehicles that drive more miles per year – all in an effort to minimize the uncertainty in the fuel consumption of the average fleet vehicle. Examination of the counts of vehicles in Column L shows this trend is present.

Vehicles would be selected from the pool of eligible vehicles so that the required numbers of vehicles as defined by the allocations in Column L are met. Table 3-4 gives the sources of information that would be used to ensure that each vehicle is placed in the proper stratum. Column L also shows that for several of the 12 strata, the number of vehicles is less than one. In these cases, clearly at least one vehicle would need to be sampled in each stratum. However, our experience indicates that it may be prudent to sample at least five vehicles in each stratum just so that an occasional wild result on the sole vehicle representing a stratum does not unduly influence the overall average fuel consumption estimated for the fleet.

Table 3-3 also shows the projected results in Columns M and N if the sample structure in Column L were applied to the information in all of the earlier columns. The overall results are given at the bottoms of Columns M and N in the boxes. The results show that the population mean of 736 gallons per year has an uncertainty (standard deviation) of 37 gallons per year, which is a coefficient of variation of 5%. This coefficient of variation is the lowest possible coefficient of variation for a sample size of 100 port-fuel-injection vehicles given all of the (artificial) values in Table 3-3.

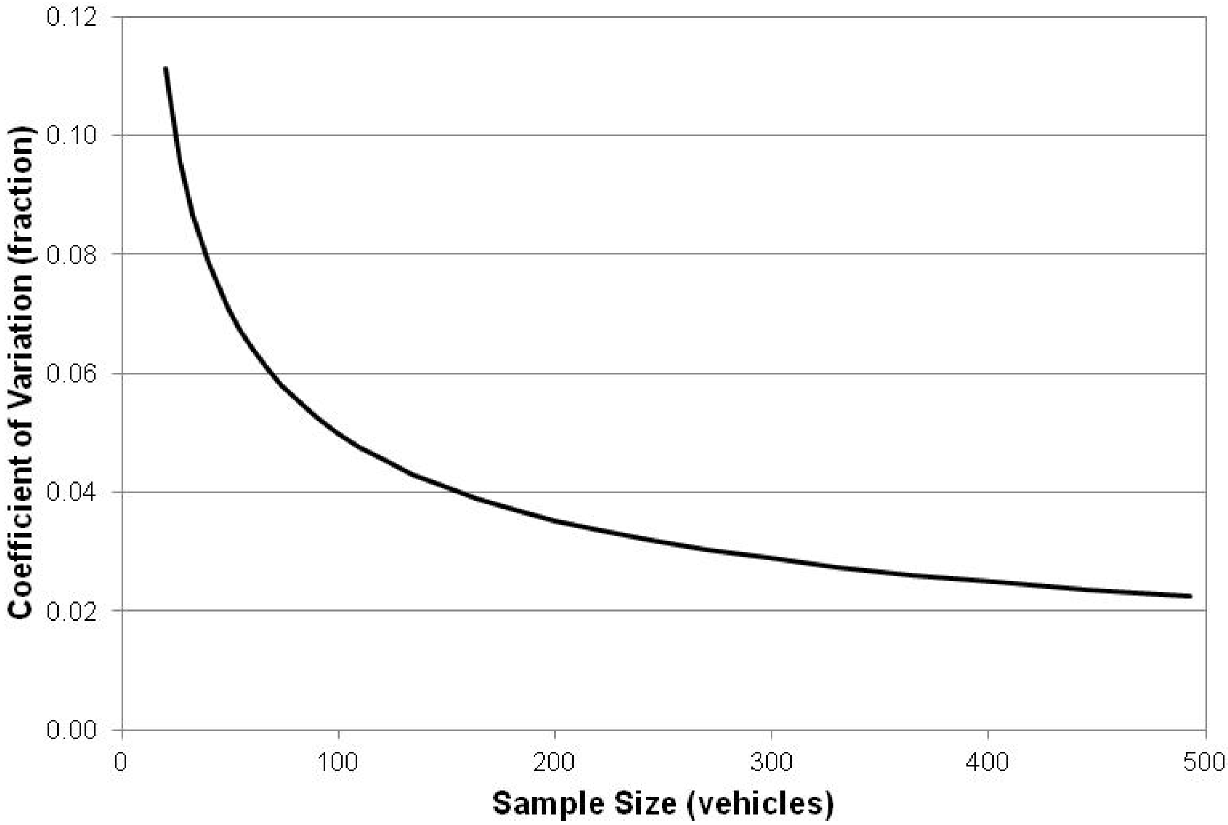
Sample size effects – The coefficient of variation is inversely proportional to the square root of the sample size. Therefore, a sample size of 400 would produce an expected coefficient of variation of 2.5%. Increased sample sizes reduce the uncertainty in the population mean gallons per year by sampling more vehicles in each of the 12 strata and, thereby, reducing the variabilities for the averages of each stratum.

Figure 3-1 provides a visual indication of the influence of sample size on the uncertainty in the average annual fuel consumption for this particular stratified binning structure shown in Table 3-3. Keep in mind that the values used in Table 3-3 are artificial, and therefore Figure 3-1 should not be used to choose a sample size for the main study.

The calculations and structure of the vehicle sample, as presented in Table 3-3, can be considered as a beginning point for designing a sample for the main study. By using the spreadsheet from which this table was constructed, the effects of changing various quantities in the table on the population mean gallons per year and its uncertainty can be examined. For example, the spreadsheet clearly shows that moderately increasing the number of vehicles in strata that have a small number of vehicles in Column L produces only a tiny reduction in the coefficient of variation.

De-stratifying the results – Once all of the measurements on the vehicles in the sample have been taken, the results can be weighted to reflect the expected trends in the national fleet. Table 3-4 provides guidance on information sources for de-stratification, which are the same sources that were used for creation of the stratified design. De-stratification would strictly apply only to the three stratification variables: propulsion system, FEEL Composite value, and annual miles driven unless some of the eleven fleet representative variables have also been stratified.

Figure 3-1.[21] Effect of Sample Size on Relative Uncertainty of the Sample Design Shown in Table 3-3



3.2.2 Stratification Plan 2 – Quantifying Influences on Instantaneous Fuel Economy: Propulsion System, FEEL Highway MPG, FEEL City/Highway

This second alternative for stratification of the vehicle sample focuses on creating a dataset that can be used to quantify the influences of various factors on the fuel economies of a wide range of vehicle technologies and fuel economy tendencies. With that goal in mind, the development of the vehicle sample considers the number of vehicles in the sample set and the types of vehicles that should be allocated to different strata in the sample set structure. For an individual vehicle, an analysis of the second-by-second fuel economy data would estimate the coefficients in the following equation which expresses the fuel economy of the vehicle in terms of a Taylor series expansion about reference values for each of the factors that influences the fuel economy:

$$FE = FE^\circ + (\partial FE/\partial x_1)*(x_1-x_1^\circ) + (\partial FE/\partial x_2)*(x_2-x_2^\circ) + \ldots \qquad \text{Equation 1}$$

[21] C:\Documents and Settings\Tdefries\My Documents\ICCT Pilot\SamplSizeEffects.xlsx

The superscript ° denotes values at reference conditions. The choice of reference conditions, which is arbitrary, might be chosen near the most common operating conditions in the dataset. FE° denotes the fuel economy at reference conditions. $x_i°$ denotes the reference-condition value of independent factors. The partial derivative $\partial FE/\partial x_i$ is a coefficient that estimates the influence of the independent factor x_i on the in-use FE.

The coefficients for some fuel economy factors may have approximately the same values across all vehicles while the coefficients for other fuel economy factors may be vehicle-dependent or dependent on the fuel economy tendency of the vehicle which may be approximated by the FEEL Composite value and the FEEL City/Highway ratio. Thus, to have a chance of determining the variety of influences of fuel economy factors on the fuel economies of different types of vehicles, a wide variety of vehicle technologies and fuel economy tendencies would need to be in the vehicle sample.

In this situation, creating an optimal stratified random sample set, as was used for Stratification Plan 1, may not be appropriate. A different approach can be used.

Select stratifying variables – A stratification design that covers a wide range of technologies and fuel economy tendencies can be made up of the following variables, which were indicated with S2 in the third column of Table 3-1:

- Propulsion System – This categorical variable has values of PFI, GDI, hybrid, and diesel. It should be used as a stratification variable because different propulsion systems can respond differently to fuel economy factors. Of course, for the main study the number of propulsion system categories can be reduced or expanded, depending on desired analyses of specific technologies (such as turbocharging and automated manual transmissions).

- FEEL Highway MPG – This variable is currently the best single value that estimates the high fuel economy potential of the vehicle under relatively steady-state operating conditions. Factors that would produce relatively short term deviations in fuel economy would deviate from a value near this FEEL Highway value.

- FEEL CityMPG/HighwayMPG ratio[22]– As discussed in Section 2, this ratio will be associated with the fuel economy effects of low speed, high acceleration, and road grade relative to the FEEL Highway value. This ratio will also be related to powertrain design and to the power/weight ratio of the vehicle.

[22] The FEEL City/Highway ratio is a better choice for a stratification variable than FEEL City MPG in this situation because the ratio is a measure of the effectiveness of strategies that strive to provide high fuel economies under high load and transient operating conditions and a measure that is independent of the overall fuel economy of the vehicle.

A sample design such as the one shown in Table 3-5 can be used to create a vehicle set with the expected data analysis in mind. The table has a separate sub-table for each of the propulsion systems and each sub-table has 20 bins that are combinations of FEEL Highway value and FEEL City/Highway ratio. The number of bins for each propulsion system and the definition of each of the combination bins are subject to change as further information about the distribution of vehicles in the U .S. fleet is obtained.

The total number of vehicles called for by the structure in Table 3-5 is 260 vehicles. These vehicles have been allocated with an equal number to each of the 20 bins within propulsion system type. The reason for this is that the goal of the design is to cover a full range of fuel economy tendencies within each propulsion system type. Thus, the strategy for Stratification Plan 2 is quite unlike for Stratification Plan 1, which was designed to minimize an uncertainty on a measured fleet quantity. For Stratification Plan 2, the goal is merely to ensure that a wide variety of technologies as defined by Propulsion System, FEEL Highway MPG, and FEEL City/Highway ratio are being instrumented so that the analysis of the second-by-second data will be able to reveal the dependence of the fuel economies of those technologies on changes in vehicle operating conditions. Accordingly, the number of vehicles allocated to Propulsion System, FEEL Highway MPG, or FEEL City/Highway ratio strata is not calculated based on variances of any quantities as it was for the strata for Stratification Plan 1. Instead, vehicles are allocated to the strata as equally as possible for a given sample size.

The number of vehicles to be instrumented for each of the Propulsion Systems is tied to the fleet's vehicle fraction in each of the Propulsion Systems and to the methods used to recruit vehicles, a vision of which is discussed in Section 4.2 below. Based on that analysis, the number of vehicles targeted in the Propulsion System strata for PFI, GDI, hybrid, and diesel vehicles could be 160, 60, 20, and 20, respectively. The goal is to make the allocations sparser in PFIs (61%) and richer in GDIs, hybrids, and diesels (23%, 8%, and 8%) than the estimated fractions of PFIs, GDIs, hybrids, and diesels in the 2013 fleet (92%, 5%, 2%, 1%) so that the sample will contain an adequate number of vehicles of all four technologies to support analyses of the effects of operating environment on fuel economy of all technologies.

Vehicles would be selected from the pool of eligible vehicles so that the required numbers of vehicles as defined by the allocations in Table 3-5 are met. Table 3-6 gives the sources of information that would be used to ensure that each vehicle is placed in the proper stratum.

Table 3-5. Vehicle Sample Structure for Stratification 2

PFI Vehicle Stratification		
FEEL Highway (mpg)	FEEL City / FEEL Highway (mpg/mpg)	PFI Vehicles
≤ 16	< 0.66	8
	0.66 to 0.72	8
	0.72 to 0.80	8
	> 0.80	8
17 to 21	< 0.66	8
	0.66 to 0.72	8
	0.72 to 0.80	8
	> 0.80	8
22 to 25	< 0.66	8
	0.66 to 0.72	8
	0.72 to 0.80	8
	> 0.80	8
26 to 31	< 0.66	8
	0.66 to 0.72	8
	0.72 to 0.80	8
	> 0.80	8
≥ 32	< 0.66	8
	0.66 to 0.72	8
	0.72 to 0.80	8
	> 0.80	8

GDI Vehicle Stratification		
FEEL Highway (mpg)	FEEL City / FEEL Highway (mpg/mpg)	GDI Vehicles
≤ 19	< 0.64	3
	0.64 to 0.69	3
	0.69 to 0.75	3
	> 0.75	3
20 to 24	< 0.64	3
	0.64 to 0.69	3
	0.69 to 0.75	3
	> 0.75	3
25 to 28	< 0.64	3
	0.64 to 0.69	3
	0.69 to 0.75	3
	> 0.75	3
29 to 33	< 0.64	3
	0.64 to 0.69	3
	0.69 to 0.75	3
	> 0.75	3
≥ 34	< 0.64	3
	0.64 to 0.69	3
	0.69 to 0.75	3
	> 0.75	3

Hybrid Vehicle Stratification		
FEEL Highway (mpg)	FEEL City / FEEL Highway (mpg/mpg)	Hybrid Vehicles
≤ 21	< 0.79	1
	0.79 to 0.94	1
	0.94 to 1.09	1
	> 1.09	1
22 to 29	< 0.79	1
	0.79 to 0.94	1
	0.94 to 1.09	1
	> 1.09	1
30 to 37	< 0.79	1
	0.79 to 0.94	1
	0.94 to 1.09	1
	> 1.09	1
38 to 53	< 0.79	1
	0.79 to 0.94	1
	0.94 to 1.09	1
	> 1.09	1
≥ 54	< 0.79	1
	0.79 to 0.94	1
	0.94 to 1.09	1
	> 1.09	1

Diesel Vehicle Stratification		
FEEL Highway (mpg)	FEEL City / FEEL Highway (mpg/mpg)	Diesel Vehicles
≤ 18	< 0.69	1
	0.69 to 0.74	1
	0.74 to 0.80	1
	> 0.80	1
19 to 26	< 0.69	1
	0.69 to 0.74	1
	0.74 to 0.80	1
	> 0.80	1
27 to 35	< 0.69	1
	0.69 to 0.74	1
	0.74 to 0.80	1
	> 0.80	1
36 to 42	< 0.69	1
	0.69 to 0.74	1
	0.74 to 0.80	1
	> 0.80	1
≥ 43	< 0.69	1
	0.69 to 0.74	1
	0.74 to 0.80	1
	> 0.80	1

Table 3-6. Information Sources for the Vehicle Sample for Stratification 2

Factor	Sources of Information for:	
	Sample De-Stratification	Sample Vehicle Selection
Propulsion System	Registration data + VIN	Survey: VIN
FEEL Highway MPG	Registration data + fueleconomy.gov	Survey info + fueleconomy.gov
FEEL City/Highway ratio	Registration data + fueleconomy.gov	Survey info + fueleconomy.gov

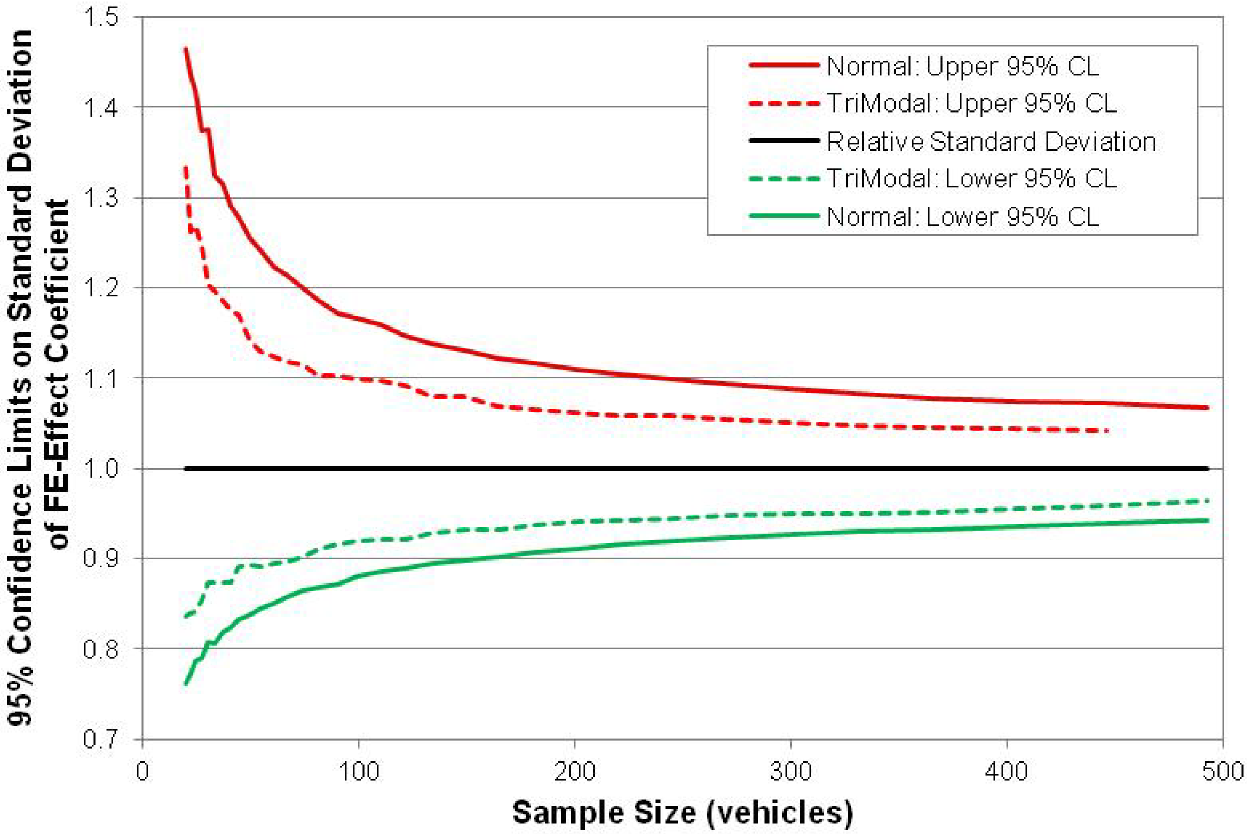
Sample size effects – In this sample design, increasing the number of vehicles assigned to each of the stratification bins provides a larger number of vehicles for which the fuel economy factor coefficients (the $\partial FE/\partial x_i$ in Equation 1) can be quantified.

The analysis of the second-by-second fuel economy of a single vehicle would produce a single estimate of a coefficient with an uncertainty for that estimate for each different fuel economy factor. Similar analyses on all of the vehicles in the dataset would produce the same sort of results. Thus, for a given fuel economy factor, for example, road grade, the analyses would produce an estimate of the coefficient from each of the vehicles in the dataset and, thereby, create a distribution of the coefficients for each fuel economy factor. Increasing the number of vehicles in the dataset would more clearly define the distribution of coefficients for each factor and also provide an opportunity to perform analyses that determine why the coefficients for each factor are different for different vehicles.

If the distribution of coefficients for a given fuel economy factor are sampled from an underlying distribution of factors, then increasing the number of vehicles in the sample set better defines the underlying distribution. Note that here we are assuming that the underlying values for a given fuel economy factor is not a constant but is a distribution and that the goal of the analysis is to define the shape of that distribution. One measure of a distribution's width is the standard deviation of the distribution. Increasing the sample size reduces the uncertainty in a standard deviation. The X^2 statistic describes how the uncertainty in the standard deviation changes with changes in sample size. The use of the X^2 statistic for this purpose strictly applies only to normal distributions. It is not known whether the distribution of coefficients for each of the various fuel economy factors is normal. Therefore, we must assume, or otherwise show, that the trend in the uncertainty of a standard deviation can be reasonably approximated with the X^2 statistic.

The solid red and green curves in Figure 3-2 show the effect of changing sample size on the upper and lower 95% confidence limits of the standard deviation of a normal distribution. These theoretical calculations were made using the X^2 statistic. The plot shows, for example, that for a sample size of 200 vehicles the observed standard deviation of a fuel economy factor would be between 91% and 111% of the true value of the standard deviation 95% of the time. The plot shows that as the sample size decreases, the confidence limits of the standard deviation get wider, and as the sample size gets larger, the confidence limits get narrower. The figure also shows that the effect of sample size on the confidence limits is relatively weak. For example, for a sample size of 400 vehicles, the confidence limits are about 94% and 108% of the true value of the standard deviation.

Figure 3-2.[23] Effect of Sample Size on Relative Uncertainty of the Standard Deviation of a Normal and a TriModal Distribution



We wrote a SAS program that simulated the reduced uncertainty in the standard deviation of a normal distribution as the number of observations is increased. The results of that simulation agreed with the theoretical effect using the X^2 statistic, which are shown by the solid red and green curves in Figure 3-2. Then, to test the effect for a non-normal distribution, we modified the SAS simulation program to use a tri-modal distribution (made up of three normal distributions) instead of a normal distribution. The results for the tri-modal distribution are shown with the red and green dashed curves in Figure 3-2. For the tri-modal distribution, at a given sample size the confidence limits on the standard deviation calculated from the sample is narrower than for the

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[23] P:\ICCT_FE_Pilot\SampleSize\SimVarUnc_1.sas via C:\Documents and Settings\Tdefries\My Documents\ICCT Pilot\SamplSizeEffects_withTriModal.xlsx

normal distribution. However, the change in the confidence limits for the tri-modal standard deviation changes by about the same relative amount as for the normal standard deviation.

Thus, we get a sense that whether the underlying distribution of the coefficients for a fuel economy factor is normal or not, the trend of decreasing uncertainty as sample size increases is similar to the trends seen in Figure 3-2. Figure 3-2 can thereby be used as a method to approximately judge the effect on fuel economy factor coefficients for the Stratification 2 approach.

Destratifying the results – The results from the Stratification 2 design can be de-stratified to reflect the expected trends in the national fleet. The vehicle counts in the stratification design shown in Table 3-5 were arbitrarily allocated rather than based on a detailed analysis of U.S. fleet distributions and variances. Nevertheless, because the results from the second-by-second data collection will need to be destratified to avoid a bias that would be incurred if the results were used directly, the U.S. fleet's proportions of the bins of the three stratification variables need to be determined to guide the weighting that will used for de-stratification. The three stratification variables were: Propulsion System, FEEL Highway MPG, and FEEL City/Highway ratio. De-stratification needs to consider only these three variables unless some of the 11 fleet representative variables have also been stratified. As shown in Table 3-6 for de-stratification, Propulsion System for the national fleet can be estimated by evaluating a sample of registration data from several states. The FEEL Highway values of vehicles in the national fleet can be obtained by matching vehicle year, make, and model for several sets of state registration data with values reported in fueleconomy.gov for those vehicles. The same can be done for the FEEL City/Highway ratios. The result of those determinations would be a weighting factor for each of the 80 bins in the vehicle sample structure shown in Table 3-5. Those weights would be applied to results obtained for each of the individual vehicles in a given bin.

3.2.3 Comparing the Two Stratification Methods

The two alternative stratification plans described in the previous two subsections differ in their goals. Those are just two of many possible goals that could be used for producing a stratified, random sample of vehicles for the main study.

The goal of Stratification Plan 1 is to minimize the uncertainty in the average annual fuel consumption of a light-duty vehicle. To meet this goal, an optimal stratification plan is called for. To minimize the uncertainty in the average annual fuel consumption, Stratification Plan 1 gives higher preference to sampling vehicles that 1) dominate the fleet, i.e. those that have middle composite FEELs, 2) vehicles that are driven more miles each year since they use more fuel each year, and 3) vehicles that have lower fuel economies since they have a higher fuel consumption rate.

The goal for Stratification Plan 2 is quite different from the goal of Stratification 1. The goal in this case is to produce a dataset that can be used to quantify the influence of different factors on fuel economy and to determine how fuel economy varies for a variety of vehicle technologies under actual, routine use, that is, not on a chassis dynamometer. While the conditions under which vehicles are driven can differ greatly from vehicle to vehicle, any individual vehicle – regardless of technology – could be exposed to any set of conditions, depending on driver behavior, vehicle use, road conditions, road terrain, and weather. On the other hand, how the vehicle responds to driving conditions is dependent on the vehicle's design and technology. Thus, the goal of Stratification Plan 2 addresses the response of individual vehicles. In this instance, an optimized stratification plan is not called for. Data from every vehicle in the sample set – regardless of FEEL or propulsion system – contributes to defining the link between driving conditions, vehicle and engine characteristics, driver behavior, and fuel economy. More variety in vehicles, engines, and conditions provides more opportunities for learning about the influences of various factors on instantaneous fuel economy. Stratification 2 does not emphasize any particular technology or fuel economy tendency, for example, as determined by composite or highway FEEL values.

Stratification 1 investigates the effects of propulsion system on fuel economy but it does not make any particular effort to stratify the effects of technology within a propulsion system on fuel economy. For example, the effects of a very advanced hybrid system versus a rudimentary hybrid system would only be examined under Stratification 1 design if representatives of those two systems would be sampled by chance. On the other hand, Stratification 2 specifically targets different technologies within propulsion system by using the ratio of the FEEL City MPG to the FEEL Highway MPG. Because this variable is built into the Stratification 2 plan, a variety of technologies within propulsion system can almost be guaranteed of being in the vehicle sample set.

In spite of their differences, both Stratification Plan 1 and 2 are stratified, random designs. Because each set of vehicles is stratified, the analyses performed on a set must always account for the stratification – otherwise, the results of the analyses could be biased.

3.3 Alternatives for U.S. Representation

Once the vehicles have been tentatively selected for the instrumented vehicle sample, the ability of the vehicle sample to represent the U.S. fleet needs to also be considered. Section 4.2

will describe the details of how the recruitment methodology would be used to make adjustments in the selection of the vehicles for the sample set to achieve the desired representation of the U.S. fleet. This section considers two alternatives for how the sample set can represent the U.S. fleet. Both alternatives would consider all of the U.S. fleet representative variables, which are listed in Table 3-2.

3.3.1 Representation 1: Proportionate Representation

The first option for U.S. fleet representation strives to select vehicles for the vehicle sample set such that the sample set mimics the relative proportions of the 11 representative variables that describe the U.S. fleet, as described in Table 3-2. We refer to this as proportionate representation.

To produce a sample set that has the same relative proportions of the 11 representative variables as the fleet, the distributions of these variables in the U.S. fleet needs to be known before the sample is created. Table 3-2 provides a suggested source for determining each of the distributions for the 11 factors. The 2010 Census results provide human population counts by zip code. By making an assumption that the vehicle population is proportional to the human population across zip codes, the altitude, the precipitation distributions, and the temperature distribution from climatological data for each zip code can be weighted by human population to arrive at an estimate of the national distributions of altitude, precipitation, and ambient temperature to which the U.S. fleet is exposed.

As will be described in Section 4.2, vehicles would be randomly selected, tentatively at first, to fill each of the bins in the stratification structure. Next, the zip code where each vehicle resides would be used to determine the altitude, precipitation and temperature distributions for the tentative vehicle sample set. The distributions for the other eight factors listed in Table 3-2 would also be determined for the tentative vehicle sample set based on information provided by the vehicle owners. If the distributions of the 11 representative variables for the sample set are similar to the distributions for the national fleet, then the tentative sample set would become the final sample set. If the distributions do not agree, then some vehicles that were initially tentatively selected would be replaced by other vehicles from the participant pool until the sample set distributions and the national distributions agree.

3.3.2 Representation 2: Enrichment of Selected Representation Variables

For this alternative representation, the proportion of one or more representative variables of the sample set can be modified to shift the distribution relative to the distribution of the variable in the national fleet. For example, perhaps only 5% of national driving occurs at altitudes greater than 5,000 feet. If the sample set vehicles were chosen proportionally to altitude category, only about 5% of the vehicles would be instrumented for high altitude driving using Representation 1 Method. With the Representation 2 method, the fraction of vehicles in the sample set that reside at altitudes greater than 5,000 feet could be increased to perhaps 10%, for example. This sort of modification to the distributions of representative variables in the sample set relative to the national fleet would result in more data from vehicles under more extreme conditions than would be obtained using the proportionate representation. Vehicles representing these more extreme values would be included in the sample set at the expense of vehicles representing less extreme values of the representative factors.

The distribution of almost any of the representative variables could be altered using this technique. Top candidates for enriched representation would be Vehicle Age: older vehicles, Transmission Type: manuals, Total Accumulated Miles: higher mileage vehicles, Driver Age: very young and very old drivers, Socio-Economics: drivers from poor households and wealthy households, Altitude: high altitudes, and Ambient Temperature: very low and very high temperatures. Enriched representation for Car/Truck, Manufacturer, Driver Gender, and Precipitation are less desirable candidates because those factors have either a multitude of levels, are expected to have small influences on fuel economy, or all levels are expected to be well represented without using enriched representation.

3.3.3 Comparing Two Methods of U.S. Representation

The U.S. fleet representation characteristics of the vehicle sample would be produced through adjustments in conjunction with the selection of vehicles to fill the stratification binning structure. Two alternative stratification binning structures were presented in Section 3.2. The 11 factors listed in Table 3-2 can be used as characteristics of the U.S. fleet. In the previous two subsections, alternative slants on the sample sets fleet representation were 1) proportionate representation, and 2) enriched representation. Each alternative has a number of advantages and disadvantages.

Development of a sample using proportionate representation is somewhat easier to produce then enriched representation. The reason for this is that the balance of representation in the sample needs to be produced essentially simultaneously with the assignment of vehicles to the different strata in the stratification binning structure. For proportionate representation, a random selection of vehicles assigned to each stratification bin would likely lead to an overall representation of the entire sample set so that it approximates the national fleet. Some minor adjustments in the vehicles selected for the sample set in individual bins may need to be made to ensure that the representation of the sample is proportionate to the national fleet. On the other hand, enriched representation – especially if several factors would be enriched – would need to be initially produced by using weighting factors for those vehicles that represent the portion of each factor that is to be enriched. For example, if older vehicles are to be enriched in the sample set, then a random sampling weight greater than one would be assigned to those vehicles so that when vehicles were randomly selected, older vehicles would have a greater chance of being admitted to the sample set. This technique would work and the weighting factors could be used during analysis to destratify the results for the entire sample set with respect to the enhanced representative factors.

With proportionate representation, the data that would be obtained in the main study would represent the distribution of values for each of the 11 representative factors. More data would be obtained under conditions where the majority of the fleet operates in comparison with the extreme conditions. On the other hand, with enriched representation, more data would be obtained under extreme conditions relative to the amount of data that would be obtained had proportionate representation would be used. Thus there is a tradeoff between gaining more information at extreme conditions versus gaining more information at conditions that the majority of the fleet is exposed to.

Because of this tradeoff, an analysis of data on the sample set following proportionate representation would reflect the trends experienced by the majority of the fleet. On the other hand, an analysis of a sample set produced by enriched representation would contain relatively more data at extreme conditions and, therefore, would produce analysis results that are more reliable for these extreme conditions while the trends in more common conditions where the majority of the fleet operates would be slightly less reliable.

Another aspect of the influence of representation that needs to be considered is the ease of destratifying the results of the main study. If proportionate sampling is used, then the results need to be destratified only for the destratification variables. However, if enriched representation is used, the results need to be stratified for any of the 11 representation variables that were enriched as well as the stratification variables. This adds extra complexity to the destratification process.

The last feature to consider is the effect of the representation alternative on the distribution of other fuel economy influencing factors. If proportionate representation is used, then the distributions of the following factors in the dataset would be approximately representative of the occurrence of these factors in the U.S. fleet: vehicle acceleration, throttle position, vehicle speed, engine warm-up status, A/C compressor status, road grade, altitude, wind, precipitation, and ambient temperature. If enriched representation is used, the distributions of these factors as measured on the vehicle sample set would be skewed by the enrichment. To determine the distribution of these fuel economy influencing factors for the fleet would require destratification of the distribution observed in the sample set data using the enrichment weighting factors. This could be done but it would involve an additional level of complexity in comparison with the distributions obtained with the proportionate representation alternative.

4.0 Vehicle Recruitment Methodology and Participant Maintenance

This section describes a method that could be used to recruit vehicles for a main instrumentation study. Section 4.1 describes several alternative sources of candidate vehicles. Section 4.2 describes in some detail one method that could be used to recruit vehicles. Section 4.3 presents several descriptions of recruitment tools that could be used for that method. Section 4.4 reviews a few alternatives for validating portions of any vehicle recruiting methodology. All of the methodologies and tools discussed in Section 4 should be viewed as a way to stimulate thought and discussion of techniques for vehicle recruiting. The intent of the discussion is not to present a final methodology.

4.1 Sources of Participant Candidates

In the fuel economy main study, a set of 1996 and newer light-duty on-road vehicles would be instrumented to collect second-by-second data on fuel economy and high temporal resolution data on the major factors that affect fuel economy. The vehicles to be instrumented need to in some manner represent the distribution of vehicles, driving behaviors, and driving conditions that represent the U.S. light-duty fleet. This goal for the sample set implies that the sampling method addresses the following two properties:

- Randomness – Some aspect of randomness needs to be present in the selection of individual vehicles. This could mean that either vehicles are selected randomly or that stratified, random sampling should be used.

- National Coverage – So that the sample set can represent the U.S. fleet, the sample frame from which individual vehicles are sampled should include all light-duty vehicles in the 50 states and the District of Columbia. Other alternatives are also possibilities. For example, vehicles could be selected from the major regions of the United States or from representative metropolitan areas and urban areas within the United States if they can be shown to be representative of the national fleet.

The discussion below presents four alternative sources from which individual vehicles for the sample set could be obtained. Each alternative source has different qualities. A summary of the advantages and disadvantages of each alternative source will be discussed in Section 4.1.5. Estimates of the costs to obtain a given sample set size will be presented in Section 6.1.

4.1.1 Source 1: Project Household Survey by a Project Team Company

In the first alternative a national survey would be conducted to identify individual vehicle candidates for instrumentation. NuStats, a team member on this pilot study, has performed many of these types of surveys.

The methodology for developing and performing a project survey could include the following steps.

1. Obtain a list of randomly selected land line and cell phone telephone numbers.
2. Obtain mailing addresses that correspond to each of the telephone numbers.
3. Mail a postcard to each of the addresses alerting the resident that they will be called to gain their participation in the study.
4. Conduct a telephone interview with each of the households using a script developed specifically for the survey.

Variations on the above process could also be used. For example, the postcard could provide an opportunity for the respondent to answer the survey questions online, and those targeted households that do not respond online could be followed up with a telephone interview.

The purpose of the script is to describe the project to the interviewee, to determine if any of the household vehicles is eligible for the study and, if the household would be willing to participate,[24] to obtain some initial information about the household, drivers, and vehicles. Note that at this point an incentive would not be offered in an effort to get the household to agree to participate since the project staff would not yet know if any of the household's vehicles would be desired for inclusion in the sample. The telephone script would need to be developed, tested, and refined for effectiveness at the beginning of or before the main study. Effectiveness is determined by doing cognitive testing in which a draft script is administered one-on-one to a small group of individuals, who are unfamiliar with the project.

Past experience indicates that the willingness-to-participate rate for this type of survey, where "cold calls" are made, will be about 5 to 10%. Therefore, approximately 20,000 to 40,000 interviewee contacts would need to be made to obtain a 2000-vehicle pool of willing participants

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[24] At this point in communicating with interviewees, the goal is to determine if the interviewee is willing to participate. In this pilot report, we strive to make a distinction between willing to participate and agreeing to participate. Willing to participate means that interviewees do not outright reject the possibility of participating; interviewees would consider participation if a future-offered incentive were acceptable to them. Agreeing to participate means that the interviewee was offered an incentive and agrees to participate in the study in return for the incentive.

from which the final sample set would be chosen. As described in Section 4.2, interviewees who are not willing to participate would be "placed" in a non-response pool. Using that pool, an analysis could be conducted to compare interviewees who were willing to participate with those who were unwilling to participate to determine if a bias existed between those two sets of interviewees.

4.1.2 Source 2: Empanelled Survey by a Surveying Company that Maintains Panels

A second alternative is to use a surveying company that maintains panels of respondents for use in conducting surveys for the company's clients. Such companies conduct a wide variety of surveys – not just surveys related to travel. For this source alternative, the surveying company would not be a member of the study's team but would be contracted specifically to conduct a survey for the purposes of generating the willing-to-participate pool. Example surveying companies include Knowledge Network and SSRS.

Knowledge Network, for example, maintains two types of panels to answer survey questions for clients. Members of the first type of panel, which can be designated as the Pristine Panel, are carefully and statistically recruited by Knowledge Network using an address based sample that gives all households that receive postal mail a chance to be included. Members of the Pristine Panel are selected to meet strict Knowledge Network criteria. By agreeing to be a panelist they are given free Internet access and a computer to ensure that even households without Internet access are included. They generally serve as panelists for a relatively long period of time – often for several years. Knowledge Network collects a wealth of economic, social, and demographic data on each of its panelists and the panel itself is representative of people in the United States. In addition, the panel is large enough that it can be used to select representative sub-populations, for example, Hispanic consumers. During their tenure, members of the Pristine Panel are administered many different surveys by Knowledge Network staff for the company's clients. Pristine Panel panelists are compensated for their participation in addition to getting free Internet service and possibly a free computer so that they can respond to the online surveys.

The second type of Knowledge Network panel can be designated as the Opt-In Panel. The Opt-In Panel has considerably more panelists than the Pristine Panel. However, the panelists are less carefully selected and less well characterized than members of the Pristine Panel. Also, Opt-In Panel members are compensated less for their services. Anybody can apply to become a member of the Opt-In Panel. Then, Knowledge Network selects a subset of applicants for empanelment. As with the Pristine Panel, panelists answer survey questions online. Even though the Opt-In Panel is selected with less statistical care then the Pristine Panel, the characteristics of the Opt-In Panel are relatively well known since the Knowledge Network has tied the characteristics and responses of the Opt-In Panel to those of the Pristine Panel. Weights are applied to results from the Opt-In Panel to approximate the results that might have been obtained from the Pristine Panel.

The Pristine Panel is one of the most scientifically rigorously selected probability sampling panels in the industry. The scientific rigor of SSRS's panel may be regarded as between Knowledge Network's Opt-In and Pristine Panels. Additionally, the panelist turnover rate for SSRS panels is higher than for Knowledge Network panels.

Knowledge Network panelists are not limited to only answering online surveys. They sometimes can physically participate in a survey, for example, for evaluating over the counter drugs. Therefore, panelists could be considered as a source of potential participants in the main study.

Because the interviewees for the Knowledge Network or SSRS surveys are already impaneled and are accustomed to answering surveys, only one step is required for this alternative in comparison with the custom household survey discussed in Section 4.1.1:

1. Conduct an online survey using a script developed specifically for the main study.

The purpose of the script would be essentially the same as for the custom household survey, that is, to determine if any of the household vehicles is eligible for the main study and, if a panelist is willing to participate, to obtain some initial information about the household, drivers, and vehicles. One advantage of using a company like Knowledge Network or SSRS, that already has existing panels, is that characteristics of each panelist are known from surveys they have taken in the past. The prime contractor for the main study would need to work with Knowledge Network or SSRS staff to develop the online questions and to evaluate cognitive testing results.

4.1.3 Source 3: Ongoing Household Travel Survey

The third alternative for a source of main study participants is to collaborate with an ongoing household travel survey. Household travel surveys are regularly made by government and private organizations. For example, Federal Highway Administration regularly conducts a household travel survey. The most recent FHWA household travel survey was taken in 2009. However, the interviewees of past household travel surveys are not likely to be available for participation in the main study because the surveys generally promise interviewees confidentiality in order to gain cooperation of the interviewee. On the other hand, ongoing household travel surveys offer a real possibility for accessing households willing to participate in an instrumented vehicle study. Because the household travel survey is ongoing, additional candidates for the main study would be obtained every month – thereby providing a continuous stream of candidates.

Acquiring participation candidates for the main study from an ongoing household travel survey has several advantages. The groundwork of developing at least part of the survey instrument and acquiring random telephone numbers would have already been done for the survey. Survey targets who endure the complete telephone survey are likely to be willing main study participants because they are apparently interested in travel and providing their travel information as demonstrated by their willingness to complete the household travel survey interview.

Another advantage is that an ongoing household travel survey would already be collecting information that would be useful to the main study for selection of the participant pool from individuals who are willing to participate. For example, the household travel survey could already be obtaining household zip code, number of vehicles in the household, and age, gender, and annual miles driven by each driver in the household. If the contractor for the main study could establish a collaborative relationship with an ongoing national household travel survey, only a few questions would need to be added to the end of the existing survey instrument to determine, for 1996 and newer vehicles, the vehicle model year, make, and model for each vehicle in the household and finally to follow up with a question of whether the household was willing to participate in the main instrumentation study.

4.1.4 Source 4: State Vehicle Registration Databases

The three alternative sources of participant candidates discussed above all begin with conversations with households and vehicle owners. For those alternatives, the descriptions of vehicles are obtained by communicating with vehicle owners. Another approach is to target vehicles of interest to the study and then to contact their owners to see if they are willing to participate. State vehicle registration databases could be used to identify the vehicles for this approach. Since vehicle registration databases have vehicle owner names and addresses, the owners could be contacted. To generate the same size pool of eligible candidates, many fewer contact may need to be made with this approach than the earlier approaches discussed because contacts would need to be made only to households that are already known to own vehicles of interest to the study. However, confidentiality of owner information in state registration databases becomes an issue.

In past projects, ERG has obtained snapshots of registration databases from state agencies. However, in general, states are quite reluctant to provide VIN and license plate information. Obtaining vehicle owner name and address information is even more restricted and sometimes requires several levels of approval before that information can be released to an outside contractor or even to another agency within the state government. We have obtained such information on occasion but only from a handful of states and the time delay in getting the information can be long and unpredictable.

We expect that many vehicle owners will not have a problem being contacted using name and address information obtained from registration databases. However, if even a few vehicle owners are upset by the release of personal information by the state, those owners could cause problems for the project.

The methodology for using registration database information would include the following steps:

1. Obtain a snapshot of the registration databases from all states or at least from a set of states that has been demonstrated to represent the U.S. fleet.
2. Randomly identify a large set of vehicles within the registration databases that would be appropriate for the main study. This would include information obtained from VIN decodes so that the propulsion system technologies and overall fuel economy tendencies of the vehicles would be known before contacting vehicle owners.
3. Determine owner telephone number from the owner name and address in the registration database.
4. Mail a postcard to each of the addresses alerting the owner that they will be called to gain their participation in the study.
5. Conduct a telephone interview with each of the owners using a script developed specifically for the main study.

Again, variations of the above process could also be considered. For example, the postcard could provide an opportunity for the respondent to answer the survey questions online and those targeted owners who do not respond online could be followed up with the telephone interview.

The purpose of the script would be similar to the survey instruments described above except that the qualities of the vehicle would already be substantially known. The script would be used to gain the cooperation of the vehicle owner in becoming a participant and, if they are willing to participate, to obtain initial information about the household and drivers. The telephone script would need to be cognitively tested for its effectiveness.

4.1.5 Comparison of Alternative Sources of Participation Candidates

This section compares the expected performance of the four alternative sources of participant candidates described above with respect to seven attributes that will be important to the cost-effective operation of the fuel economy main study. Table 4-1 shows brief notes for each of these seven attributes for each of the four alternative sources. In this discussion, the custom household survey by a project team company (Source 1) will be called the Project Household Travel Survey (Project HHTS), the custom survey by a surveying company that maintains panels (Source 2) will be called the Empanelled Survey, the ongoing household travel survey (Source 3) will be called the Ongoing HHTS, and the acquisition of lists of vehicle owners from state vehicle registration databases (Source 4) will be called the Registration Survey. These terms are underlined in the headings of the columns of Table 4-1.

The relative ranking of the four alternatives for each of the quality attributes is designated in the table by the color of the background within each cell. Green represents highest quality, yellow represents moderate quality, and red represents lowest quality among the four alternatives. Keep in mind that just because an attribute is designated as lowest quality does not mean it makes the source alternative unacceptable. In other words, any of the alternative sources could be used for the main study. In the discussion below, each of the seven quality attributes is considered for each of the four alternative sources.

Table 4-1. Attributes of Sources of Participation Candidates

Quality Attributes	**Project HHTS:** Household Survey by a Project Team Company	**Empanelled Survey:** by a Surveying Company that Maintains Panels	**Ongoing HHTS:** Ongoing Household Travel Survey	**Registration Survey:** State Vehicle Registration Databases
Cost	Moderately expensive. All aspects of conducting the survey borne by the main study. Low overhead.	Industry leaders could be quite expensive. Panel already exists. Cost sharing for panel maintenance.	Probably inexpensive. Just adding questions to end of existing survey instrument. Groundwork already provided by survey operator.	Probably expensive. State databases expected to have low purchase cost. High labor costs to contact 50 states and soothe confidentiality.
Collaboration	A project member company will have travel survey and vehicle instrumentation experience.	No benefits from collaboration; company does the work under a contract.	A survey sponsor that is already interested in travel behavior will likely also be interested in fuel economy trends.	No expected benefits to each state from collaboration with the main study.
Availability of Basic Data + Stratification Variables	Must ask for every piece of info. May make survey instrument longer.	Much panelist detailed non-travel info including demographics. Perhaps some travel info.	All info is related to travel since survey focuses on travel.	Vehicle info is available, but must ask for every piece of non-vehicle info.
Willing-to-Participate Rate	Except for postcard alerts, these will be "cold call" interviews. Expect low willing-to-participate rates.	Almost all online interviews will be completed. Expect low willing-to-participate rate since panel is not focused on travel.	Expect high willing-to-participate rates since survey is a travel survey.	Except for postcard alerts, these will be "cold call" interviews. Expect low willing-to-participate rates.
Timing + Control	Closest to absolute control since timing is controlled by the main study contractor.	Timing subject to surveying company schedule. As a client, main study contractor would have control.	Info and schedule for the main study contractor will be subject to the HHTS's sponsor.	Expect long delays to get registration data from states. Close to absolute control after that.
Bias	Small chance of bias since the main study contractor controls the survey.	Panelists are well selected, but panel has the trained respondent problem.	Small chance of bias since the survey should be well designed even though main study contractor is not the survey's primary focus. The design can be evaluated by the main study contractor.	Even though main study contractor controls which vehicles are selected, mild chance of bias exists since getting registrations from all 50 states unlikely.
Participant Retention	Same survey company used for initial screening and final empanelment.	Different survey company used for initial screening and final empanelment.	Different survey company used for initial screening and final empanelment.	Same survey company used for initial screening and final empanelment.

Cost – The Ongoing HHTS has the advantage of lowest cost. With an Ongoing HHTS, the ground work would have already been done by the sponsor. This would include determining telephone numbers and addresses and developing the main survey instrument. With the sponsor's cooperation, questions needed by the main study could be added to the end of the existing survey instrument to obtain the specific information needed by the main study to screen participant candidates and to determine if the interviewee is willing to participate in the main study. The Project HHTS would be next higher in cost because all aspects of conducting the survey would be borne by the main study. However, since the surveying company would be a member of the main study project team, relatively low overhead rates would be available. The Empanelled Survey could be quite expensive because the cost for maintaining a long term panel (for example, the Knowledge Network Opt-In panel) can be expensive even though they are shared by many different clients of the company. Additionally, Knowledge Network is considered an industry leader and can be expected to demand a premium price. An advantage of the Empanelled Survey is that the panel already exists and therefore those empanelment and maintenance costs have already been incurred. The Registration Survey is also expected to be expensive – not because the state databases would have a high purchase cost – but because the main study project team would incur high costs involved in contacting all 50 states and addressing the bureaucratic requirements needed to address the confidentiality issues of releasing vehicle owner names and addresses to the main study project team.

Collaboration – The main study project team and the organization performing the survey may benefit from the collaboration during identification of participant candidates. The Ongoing HHTS has the advantage here since the sponsor of the Ongoing HHTS is already interested in the travel behavior of the survey's respondents. Accordingly, it is likely that the sponsor would also be interested in the fuel economy trends of vehicles in the fleet and the behavior of vehicle owners in terms of driving patterns and vehicle usage, which would be obtained in the main study. The company performing the survey for the Project HHTS would be a member of the project team and would have been selected for the project team because of past experience conducting travel surveys and even perhaps performing vehicle instrumentations. Thus, the main study would benefit from the experience of the Project HHTS operator. In contrast, the Empanelled Survey and the Registration Survey operators gain no particular benefit in terms of collaborating with the main study. The Empanelled Survey company performs many types of surveys and does not concentrate on travel surveys. The states maintain registration databases but are not especially interested in the fuel economies of vehicles.

Availability of Basic Data and Stratification Variables – The basic data and stratification variables would be used to select participants from the willing-to-participate pool, would likely be used during analysis to weight the sample set results to estimate national trends, and could become independent variables with respect to measures of fuel economy. A subset of the basic data variables and potential stratification variables are particularly important to know before selection of participants from the willing-to-participate pool so that the selections can actually be made. The variables in this subset include vehicle manufacturer, vehicle make, vehicle model, vehicle age, transmission type, total odometer reading, driver age, driver gender, socio-economics, and household zip code, as well as potential stratification variables for propulsion system and annual miles driven.

The availability of this data is expected to be best for the Ongoing HHTS since this survey is likely already be designed to acquire travel information from the households. That information would just need to be supplemented by questions at the end of the survey instrument added for the purposes of the main study. The Empanelled Survey would also have additional information about the panelists and much of it would be detailed non-travel information including demographics that would have been obtained during initial consideration of the panelist for the panel. In addition, the results of earlier surveys by other clients may be available. These earlier surveys may provide some travel information. The Registration Survey alternative would have detailed vehicle information available since the registration databases will have typically model year, make, and VIN. However, for the Registration Survey alternative, every piece of household and driver information would need to be obtained using an online or telephone interview. The Project HHTS alternative has the disadvantage for this attribute since every piece of information to be obtained must be requested of the interviewee.

Willing-to-Participate Rate – The willing-to-participate rate for this discussion is regarded as the percentage of respondents who are willing to participate in the main study. Respondents who are willing to participate are those who do not outright reject any participation; they are willing to consider participation even though no incentive is yet offered. The willing-to-participate rate is an important first hurdle in the recruiting methodology. Incentives would be offered later, but only to those willing-to-participate respondents whose vehicles are desired for the sample. Again, the Ongoing HHTS is expected to have the advantage for this attribute since the survey has been designed to be a travel survey and, therefore, has a focus similar to the main study. Since the Ongoing HHTS respondents would have been selected for travel questioning and would have been alerted before the telephone interview, we expect that participation rates as high as two-thirds are possible. The Empanelled Survey would use only online interviews but because the Empanelled Survey uses a panel that is not focused specifically on travel issues, we expect a low willing-to-participate rate in the vicinity of 5 to 10%. Except for postcard alerts, the

Project HHTS and Registration Surveys would basically be cold call interviews, and therefore, we expect low willing-to-participate rates in the vicinity of 5 to 10%.

Timing and Control – Timing and control refers to the ability of the main study contractor to control the timing and response of the surveying used to identify participation candidates early in the project. The advantage here goes to the Project HHTS since the survey operator is a member of the project team. All of the survey operator's activities are designed to meet the specific and direct needs of the main study. Thus, the Project HHTS is the closest to absolute control that the main study can have over the survey activities. The next best alternative is the Empanelled Survey where the surveying company that maintains its own panel would have a contract with the project team but not be a member of the team. Still, with the main study contractor as a major client, they would still have control over the survey activities. The sponsor of the Ongoing HHTS would maintain control of their HHTS since that is the primary purpose of that survey. The sponsor might allow questions to be added to the end of their survey instrument for use by the main study. Still, the main study's desire for information and schedule would be subservient to the desires of the sponsor of the Ongoing HHTS. Finally, the Registration Survey timing could be a problem because of expected long delays to get registration data from the states. Nevertheless, once the registration data from the states is obtained, the project team would have close to absolute control.

Bias – For all alternatives, special efforts would be undertaken to minimize the bias in the pool of participant candidates produced by each alternative. In spite of this it is possible that biases can creep into the pool. Both the Project HHTS and the Ongoing HHTS are expected to have small chances of bias because the surveys are either controlled by the main study through the team member that performs the survey or would have already been addressed through careful sampling by the operator of the Ongoing HHTS. In the case of the Ongoing HHTS, the main study team can evaluate the techniques that are used to sample the population to help ensure that biases in the pool are minimized. Because it would be difficult to get registration databases from all 50 states for the Registration Survey approach, a moderate chance exists for biases in the pool generated by that technique. For the Empanelled Survey approach, the maintained panels have panelists that are carefully and well selected. However, once a person has been a panelist for substantial period of time, they may develop attitudes as a result of the many surveys that they have responded to. An evaluation of biases between those who are willing to participate and those who are not and between those who agree to participate and those who do not could be made by an analysis of the owners in the non-response pool, which will be discussed in Section 4.2.

Participant Retention – Switches in the surveying company are known to be a cause of loss of potential participants. When the pool of participant candidates is obtained by the same company as is used for the later interviews, which are used to obtain detailed vehicle information, the retention of the participant candidates in the final instrumentation pool is expected to be higher than if a different survey organization occurs. Therefore, the Project HHTS and the Registration Survey have advantages for higher participant retention than the Ongoing HHTS and the Empanelled Survey do. However, with appropriate notification to participant candidates that the company may change, the disadvantage of changing companies may be minimized.

4.2 Description of Recruitment Methodology

This section presents one option for recruiting vehicles for the main study. This option is based on selected alternatives discussed earlier in this report: the use of an ongoing national household travel survey (HHTS) as a source of candidate participants, a stratification structure based on propulsion system, fuel economy label Highway value, the ratio of fuel economy label City to fuel economy label Highway values, and characteristics of the overall sample that proportionally represents the characteristics of drivers and vehicles in the U.S.

As described in Section 4.1, an ongoing national household travel survey as a source of candidate participants is particularly attractive. Such a survey would produce monthly lists of willing-to-participate respondents, who were randomly selected across the nation. The steady monthly stream of candidates from the HHTS would allow the main study to start slowly, if necessary, to "work out the kinks" in the main study's strategy while always having a fresh pool of willing-to-participate respondents who have just recently been interviewed by the HHTS. National sampling is desirable so that the full range of driving behaviors and vehicle operating environments (weather, altitude, road conditions) would be represented in the sample. Any competently designed HHTS will strive to representatively select interviewees. In this situation, the role of the main study contractor would be to verify the adequacy of the HHTS techniques – not the much larger role of developing the techniques. Because the HHTS is a travel survey, a large fraction of the respondents who complete the survey would likely be willing to participate in the main study. The sponsor of the HHTS would be likely to collaborate with the main study sponsor since they are interested in travel, too. This mutual interest could lead to shared costs and shared data.

The flow diagram in Figure 4-1 provides an overview of the recruitment and participant maintenance methodology. Parallelograms represent owner/vehicle pools and datasets, rectangles represent activities by the project team, and gray diamonds represent decision points in the flow.

For the detailed discussion below, Figure 4-2 is an annotated version of the flow diagram that additionally provides estimated percent efficiencies at decision points, counts of the number of vehicles in black rectangles for this scenario, and tan squares (labeled 1, 2, 3, 4) that denote points where basic data is obtained. The counts in the figure were determined so that at the end of the main study, 200 participating vehicles would have generated one year of second-by-second data. The "upstream" counts were produced by back-calculating from the 200-vehicle goal using the following assumed efficiencies[25]:

- 67% of HHTS interviewees are willing to participate in the main study,
- 20% of owners who receive advance notification packages register online,
- 62% of owners who receive advance notification packages register by phone interview,
- 20% of mailed instrumentation packages cannot be installed successfully – even with assistance, and
- 25% of vehicles with successful installations do not complete a year of data collection – even with assistance.

Other assumed efficiencies would, of course, produce different upstream counts. Initial results obtained during start-up of the main study could be used to update these efficiency values and thereby adjust the counts expected in the work flow.

The yellow parallelogram in the upper left hand corner of Figure 4-2 indicates that, in this scenario, participant candidates would come from a national HHTS that is underway. The accumulation of information for Tan Square 1 begins. We assume that the survey would have information for the address, telephone number, and zip code for the respondents to that survey. This information may not necessarily be the information for the respondent's residence because some people may be interviewed while they are at work.

[25] The assumed efficiencies are educated guesses based on prior experience that contributors to this pilot study have had. Therefore, while these values are used to illustrate the recruitment method, they also represent our best estimate of what the actual efficiencies may be.

Figure 4-1. Participant Recruitment Flow Diagram

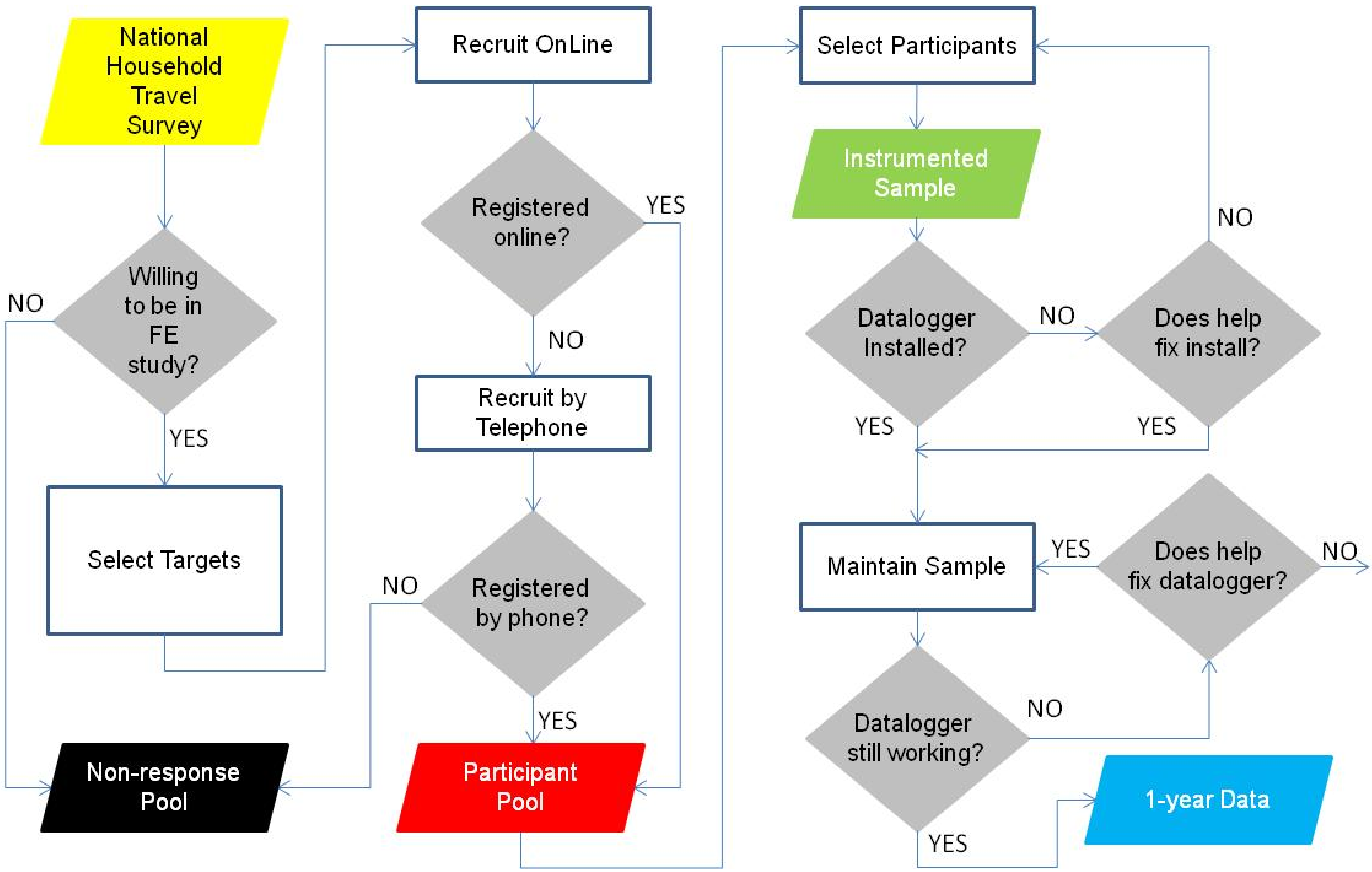
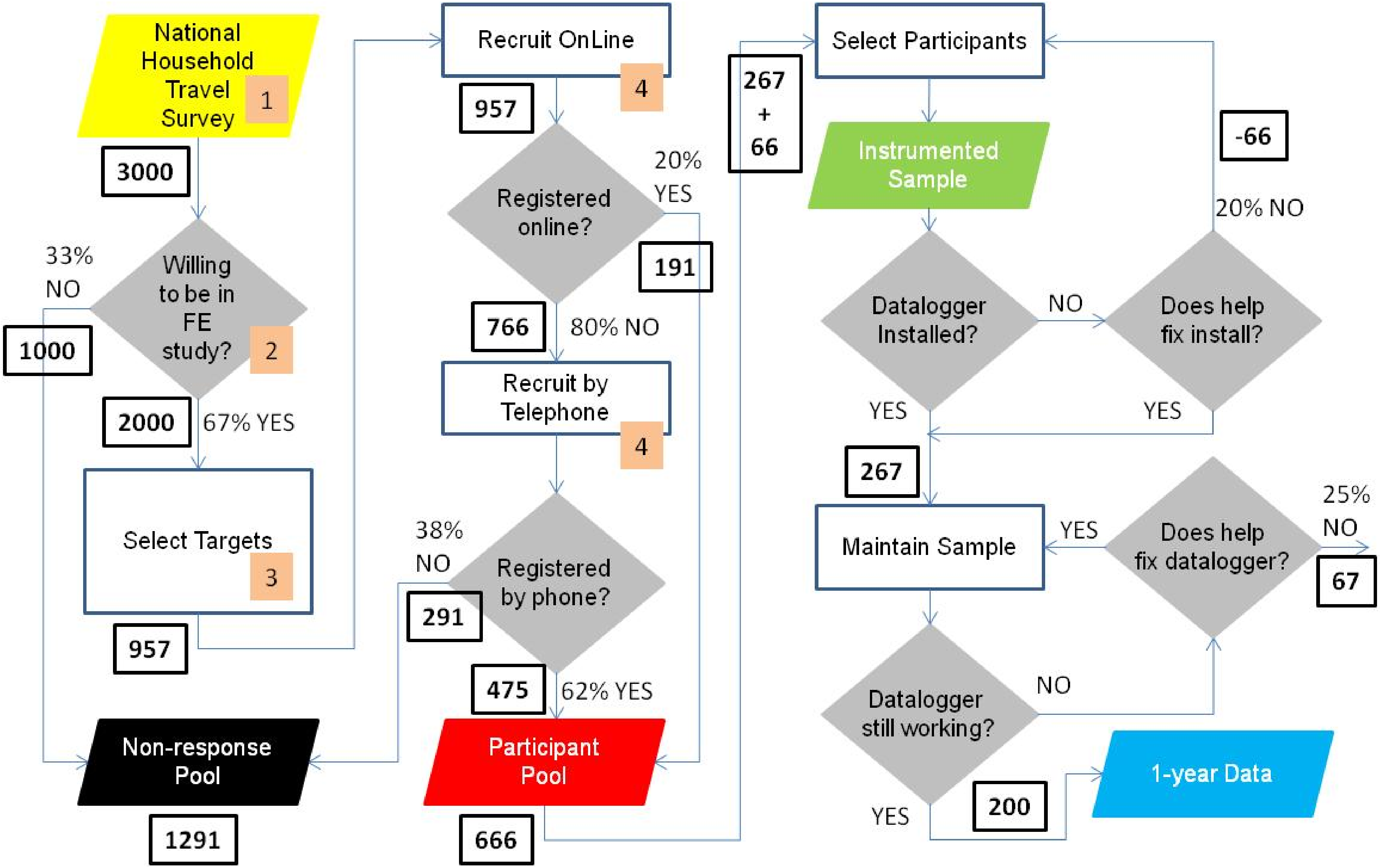


Figure 4-2. Participant Recruitment Flow Diagram with Annotations



The existing HHTS survey would obtain the following information from owners of 3000 vehicles that were model year 1996 and newer light-duty vehicles:

- Interview address, interview phone number, interview zip code
- Urban/rural measure
- Number of vehicles in household
- For each responding driver:
  - Age, gender, marital status, race, annual miles driven on any vehicle
  - Type of driver (frequent, sometimes, never)
  - Type of vehicle driven on day of the interview

With the collaboration of the HHTS sponsor, a number of questions would be added at the end of the HHTS survey instrument for the fuel economy study. These added questions would obtain important information to determine which of the HHTS respondents' vehicles would be good candidates for the main study. Clearly, adding these questions to the HHTS survey requires the collaboration of the HHTS sponsor. We expect that the HHTS sponsor would be agreeable to adding questions as long as their questions are first and the added questions do not increase the survey duration substantially. The first set of additional questions would determine (also for Tan Square 1):

- For all 1996 and newer light-duty vehicles in the household:
  - Year, make, model
  - Is it a diesel?
  - Is it a hybrid?
  - The name of the primary driver of the vehicle.

At this point, the HHTS interviewer would describe briefly the main study and ask the interviewee if they would be willing to participate in the main study. Determining willingness to participate could easily be done by the HHTS interviewer because the goal is simply to determine if the interviewee would even consider participation. A simple description of the instrumentation would be read by the interviewer. No incentives would be offered since at the time of the HHTS interview it would not be yet known if any of the interviewee's vehicles would be desired by the main study. Determining respondent's willingness to participate is shown by the gray diamond in the first column of Figure 4-2. If they answer "yes," then the survey would get this additional information for Tan Square 2:

- Name
- Home address (to mail advanced notification package)
- Home zip, and
- Telephone number (for recruiting by telephone).

If they answer “No,” then the survey would already have information on vehicle and driver that could be used to correct results and evaluate any bias for the non-response. Thus, it is key that the question, “Are you willing to participate in the fuel economy study?” be asked after all other information has been obtained.

We expect that about two-thirds of respondents to the HHTS would be willing to participate in the main study since they have demonstrated interest in travel by staying with the HHTS interviewer. The main study contractor would have to evaluate the techniques used by the HHTS to avoid bias via HHTS non-respondents. Thus, at this point 2000 vehicles move on as candidates for selection to the Select Targets box while 1000 vehicles move to the black Non-Response parallelogram at the bottom left of Figure 4-2.

In the Select Targets box, the vehicles of participants who are willing to be in the project and their households would be characterized by the project team. The vehicle would be assigned to a propulsion system bin, which would have values of 1) port fuel injection, 2) diesel, 3) hybrid, or 4) possible gasoline direct injection, or any other technology categories of interest to the main study sponsor. Most owners would know if their vehicle is a diesel or a hybrid, but fewer owners would be able to correctly identify their vehicle as port fuel injection vs. gasoline direction injection. Therefore, if the respondent said that their vehicle was either a diesel or a hybrid, it would be assigned to those propulsion system categories. If the year, make, and model of the vehicle corresponds to a year, make and model where gasoline direct injection engines were offered by the manufacturer as either standard or as an option, then the vehicle would be assigned to the possible gasoline direct injection bin. Otherwise, the vehicle would be assigned to port fuel injection. The assignments of vehicles to propulsion bins at this point would be tentative and would be firmed up later in the recruitment process based on the vehicle VIN.

Based on the owner-stated vehicle year, make and model, and fuel economy label values looked-up in fueleconomy.gov, each vehicle would be assigned to a Highway MPG bin and to a bin of the ratio of City MPG and Highway MPG. The vehicle would also be assigned to a vehicle age bin based on the model year, to a manufacturer bin (e.g., GM, Ford, Chrysler, Europe, Asia) based on the vehicle’s make, and to a vehicle type bin (e.g., car, truck, SUV,…) based on the vehicle’s year, make and model. The gender of the primary driver would be used to assign the vehicle to a driver gender bin. The zip code of each respondent would be recorded. Later, the zip code would be used to adjust vehicle selection so that the entire set of targeted vehicles has distributions of altitude, precipitation, and ambient temperatures that approximate the distributions of those quantities for the U.S. population.

At this point (Tan Square 3), the 2000 vehicles entering the Select Targets box have been tentatively assigned, based on owner-stated information, to bins for:

- Propulsion system,
- Highway MPG,
- City/Highway MPG ratio,
- Vehicle age,
- Vehicle type,
- Manufacturer,
- Driver gender, and
- Zip code (value, not a bin).

At this point, information for total odometer, transmission type, driver age, and driver socio-economics has not been obtained.

The number of vehicles assigned to each of the propulsion system bins can be estimated based on the estimated fleet fractions discussed earlier: 2% diesel, 2% hybrid, 5% GDI, and 91% PFI. Assuming that the 2000 vehicles of willing candidates are a random fraction of the population, but taking into account that the fraction assigned to the possible-GDI bin might be twice as numerous as the actual GDI fraction, the numbers of vehicles expected to be assigned to the propulsion system bins would be approximately:

- 40 diesels,
- 40 hybrids,
- 200 possible-GDIs, and
- 1720 PFIs.

In this estimate, half of the possible-GDIs would actually be GDIs, and the other half would be PFIs.

Once all vehicles and owners who expressed willingness to participate in the main study have been categorized, each of them would be assigned to one of the 20 strata that are defined by Highway MPG bin and City/Highway MPG bin within each of the four tentative propulsion system bins. Then within each of the bins, 957 vehicles of the 2000 vehicles would be randomly selected (within assigned propulsion system) so that an equal number of vehicles represents each of the 20 bins.

Because of the low numbers of diesel, hybrid, and possible GDIs in the vehicle set at this point, it would be necessary to retain all willing diesel, hybrid, and possible GDIs to maximize the number of those technologies in the instrumented vehicle sample. Thus, the following numbers of vehicles for the assigned propulsion system are expected to be randomly selected for recruitment:

- 40 diesels,
- 40 hybrids,
- 200 possible GDIs, and
- 677 PFIs.

However, since a portion of the possible GDIs (we assume half) may actually be PFIs, the counts of vehicles in each propulsion system category may actually be approximately:

- 40 diesels,
- 60 hybrids,
- 100 GDIs, and
- 777 PFIs.

Note that 2000 vehicles were obtained from the HHTS to help ensure that a sufficient number of vehicles are available to tailor the distribution of factors describing national representation.

The 957 vehicles selected in the Select Targets box would go on to be recruited online in the Recruit OnLine box in Figure 4-2 at the top of the second column. These participant candidates would be sent the advanced notification package which would encourage them to register online for the project. As described earlier and as shown in Figure 4-2, only about 20%, or 191 vehicles, of those candidates that are sent advanced notification would register online. Those 191 vehicles that do register online would be placed in the red Participant Pool parallelogram at the bottom of the second column. Those 766 vehicles that do not register online would be followed up within two weeks by the telephone recruitment process.

Both the online recruitment and the telephone recruitment would acquire the following information (for the Tan Squares 4) from the candidate who is registering to participate in the project:

- For the targeted vehicle:
  - VIN (use VIN check digit checker during VIN entry),
  - Name of primary driver,
  - Total odometer reading,
  - Annual miles accumulated (approximate),
  - Transmission type (automatic, manual),
- Targeted vehicles primary driver:
  - Age,

- Socio-economics,
- All telephone numbers,
- Primary email,
- Confirmed name, address, zip code

As usual for telephone surveying, multiple attempts (at least six) would be made to contact recruitment targets by telephone on various days of the weeks during the day, evening, and on weekends to attempt to convert the candidates into participants. Those 475 vehicles whose owners are reached by telephone and agree to participate would be placed in the red Participant Pool parallelogram at the bottom of the second column in Figure 4-2. The owners of 291 vehicles who cannot be contacted by telephone or who refuse participation would proceed to the black Non-Response parallelogram in the lower left of Figure 4-2.

At this point, the 666 vehicles that are in the participant pool are those whose owners are willing to participate in the main study, and data on the drivers and vehicles have been obtained. At this point, the propulsion system would be confirmed since the VINs of the vehicles would now be known. Assuming that the recruitment success rate is independent of propulsion system, the expected propulsion system distribution of the 666 vehicles in the participant pool is expected to be:

- 28 diesels,
- 28 hybrids,
- 70 GDIs, and
- 540 PFIs.

The bin assignments on the 666 vehicles and drivers were based on preliminary information obtained at the end of the HHTS as stated by the owners. Since updated information would be obtained during the online and telephone recruitments, these bin assignments can be updated. The members of the Participant Pool would therefore have updated vehicle and driver information including now available information for each of the vehicles and drivers for:

- Total odometer,
- Transmission type,
- Driver age, and
- Driver socio-economics.

With all of this information available for the 666 vehicles in the Participant Pool, the identification of participant candidates, which would occur in the Select Participants box at the top of the third column of Figure 4-2, can begin. The goal of the Select Participants activity would be to select from the Participant Pool 267 vehicles that have an equal number of representatives in each of the bins within each propulsion system[26] and that have distributions of the 11 proportionate variables for the 267-vehicle set as a whole that most closely approximate the distributions of the 11 proportionate variables for the nation.

Here is how the vehicle sample for instrumentation would be created. First, final assignments of all 666 vehicles to all stratification bins (combinations of propulsion system, Highway MPG bin, and City/Highway MPG ratio bin) would be made. Then, within each of the 80 bins, individual vehicles would be randomly selected to meet the bin's quota. Next, the distributions of the 11 proportionate variables for the sample would be compared with the target distributions of the nation. Finally, if the distributions of proportionate variables of the sample and the nation are not in substantial agreement, then another random selection would be made or adjustments to the individual vehicle selections within each stratification bin would be made until substantial agreement is obtained.[27]

Having a larger number of vehicles (666) in the Participant Pool than the number that are required for the instrumented sample (267) provides flexibility for filling all stratification bins and flexibility for matching the characteristics of the nation. In addition, after vehicles are removed for empanelment, the Participation Pool would contain 399 remaining vehicles that can be used, as discussed below, when the unforeseen happens to individual impaneled vehicles.

Instrumentation packages would be sent to all of the 267 selected vehicles by insured and tracked overnight courier. This would occur in the green Instrumented Sample parallelogram in the third column of Figure 4-2. Each vehicle owner would install the shipped datalogger onto his vehicle (or have the datalogger installed).

Assuming that the dataloggers would have wireless data transmission capability, successful installations can be detected by observing the beginning of data flow to the server. The third column gray diamond "Datalogger installed?" would be answered "yes" when initial signals are obtained from each installed datalogger. At this point, the flow diagram Maintain

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[26] For example, the goal might be to select 1 diesel for each of the 20 diesel bins, 1 hybrid per bin for each of the 20 hybrid bins, 3 GDIs per bin for each of the 20 GDI bins, and 8 PFIs per bin for each of the 20 PFI bins. This would make a sample that is 8% diesel, 8% hybrid, 23% DGI, and 61% PFI. Thus, the sample will be about four times richer in diesels, hybrids, and GDIs that the 2013 calendar year U.S. fleet. The advantage is that each type of propulsion system in the sample would have enough members (≥20) to provide an adequate representation of each propulsion system.

[27] Random vehicle selection does not guarantee that the distributions of the sample will look like distributions of the nation. This can occur just because of statistical fluctuations in the random selection process or it can occur because the steps used to prepare the Participant Pool may have introduced biases. In any case, if this final step is required, the vehicle sample can no longer be considered stratified random. The trade-off of this approach is that the sample will be assured of not having inadvertent skewnesses that make the sample unlike the nation, for example, a sample with 80% female drivers.

Sample box indicates that the 267 participants would be maintained for the one year datalogging period. If after a time, no data is obtained from a particular datalogger, the recruitment methodology would attempt to help the participant get the datalogger installed and data flowing. Also, if the owner has difficulty installing the datalogger, various levels of datalogger installation assistance would be available to the owner as described in the datalogger assistance paragraphs of Section 4.3. If those avenues are successful, then dataloggers that were not originally producing data would begin to produce data and would thereby move into the Maintain Sample box.

However, even after a number of attempts, perhaps 66 vehicles would not be able to successfully have dataloggers installed – even with assistance. This determination is indicated by the top gray diamond in the fourth column of Figure 4-2: Does help fix install? In these cases, the dataloggers would need to be returned to the main study team for alternate use and 66 replacement vehicles would need to be chosen from the red Participant Pool parallelogram. For each non-instrumentable vehicle, a replacement vehicle would be chosen from the same stratification bin (combination of Propulsion System, Highway MPG bin, and City/Highway MPG bin) in the participant pool. This would ensure that the replacement vehicle has similar characteristics to the vehicle that is being replaced.

Thus, with assistance with initial installations and any needed replacements from the participant pool completed, 267 vehicles would have dataloggers installed and transmitting second-by-second data. All of this would have required 333 vehicles from the participant pool. As was the case earlier, the larger number of vehicles (666) in the Participant Pool than the number required to create the instrumented sample (333) provides flexibility for replacing vehicles that cannot be instrumented.

Once the 267 vehicles have been initially instrumented, participant maintenance becomes the main focus of the recruitment procedures. On a routine basis, the dataloggers would be monitored to ensure that they are still operating properly and transmitting good quality data to the server from all vehicles in the sample. This is denoted in Figure 4-2 flow diagram by the gray diamond at the bottom of the third column. If throughout the year, all the dataloggers continue to work, one year of data would be produced for each of the 267 vehicles. However, it is likely that there will be instances when data transmission stops. When this occurs, the study team would investigate the cessation of data. This is expected to usually be a communication with the vehicle owner. In some cases, the owner may need assistance to reestablish data transmission. This assistance could be assisting the owner with reinstallation of the existing datalogger, or it could be sending the owner a different datalogger. In some cases, for example if the vehicle has been in a serious accident, the vehicle may need to be removed from the sample. If this occurs early in the one year period, the decision may be made to replace the vehicle with a new participant from the participant pool. Vehicles whose dataloggers fail after the first two months and cannot be restored would probably not be replaced with other vehicles from the participant pool unless the failures are abundant and early in the one-year period.

A portion of the vehicles that have dataloggers initially installed successfully would not produce a full one year dataset. As shown by the lower gray diamond in the fourth column of Figure 4-2, about 67 vehicles (25% of the 267 vehicles) are not expected to complete the one-year instrumentation period. If all of these estimated efficiency percentages are correct, this plan would produce one year of data for 200 vehicles.

4.3 Tools for Recruitment and Participant Maintenance

A variety of tools would be used to recruit and maintain the instrumented vehicle sample during the one-year data collection period. The tools would include: an incentive package, a project website, an advance notification package, telephone recruitment tools, datalogger assistance, and participant management tools.

Incentive package – Since this study would continue over an extended period of time, incentives should be regularly provided to study respondents to encourage their continued participation. During the shakedown phase of the main study, an evaluation should be made to determine the appropriate levels and types of incentives necessary to ensure that a sufficient number of vehicles and their owners participate in the study. Based on previous experience, incentives in the form of cash or prepaid incentive cards (for example, amazon.com or giftcertificates.com) function well to keep participants engaged in a long-term study. We know from experience that in long-term studies such as this one, offering staggered incentives for completing certain tasks or assignments on a predetermined schedule also works well to retain participants.

Given the level of complexity and effort required by participants in this study, we anticipate that total incentives ranging from \$100 to \$500 per panel participant would likely be needed; however, participants should earn a specific and preset amount at key points during the study. For example, at the point of confirmed participation (demonstrated by registering as a participant and then successfully installing the datalogger, which might be confirmed by the beginning of wireless data transfer), after successfully completing short interim questionnaires (award is based upon confirmation of successful download/delivery following data confirmation and processing), and at the end of the vehicle instrumentation phase and confirmation of return of the datalogger. During cognitive testing of the shakedown phase of the main study, the incentive amounts, the number of tasks worthy of an incentive, and the type of incentive should be further refined.

Five incentive package ideas have been put forward:

- **Monetary** – Each participant who completes the study would receive a monetary cash incentive throughout the course of the study. The first installment would be distributed at the completion of the retrieval phase to elicit immediate participation. The second installment would be mailed when the datalogger has collected half a year of data. The third and final installment would be delivered upon completion of the year-long data collection and when the datalogger has been returned.

- **Gift cards** – Participants would be given the option of receiving gift cards in the form of an incentive. A combination of gift cards would be available to allow the participant the freedom to select the incentive that works best for them. The gift cards would be distributed in the same amount and timeframe as the monetary incentive.

- **Gamification** – In conjunction with the Website, the main study would use gamification (using games) to keep participants motivated throughout the year-long study. Participants who complete the gamification process and maintain a working datalogger would be entered into a drawing for one of three iPads to be given away during different times of the study. A hotline would be set up to assist participants with questions about the study and troubleshooting techniques for the on-board diagnostic devices deployed to the participants.

- **Free AAA membership** – All study participants who successfully install the datalogger (this means that the datalogger is transmitting data and the study server receives the data) would receive a free one-year AAA membership so that participants can receive roadside assistance. If the participant drops out of the study, whether they choose to drop out or drop-out is simply beyond their control, the free AAA membership would not be renewed for the following year. Participants, whose vehicles and dataloggers successfully complete the one-year data collection period and who return the datalogger to NuStats, would receive a free second-year AAA membership.

- **Vehicle data report** – As an incentive, participants would be offered a copy of the detailed one-year data that was collected on their vehicle. This would likely be interesting, easy-to-understand graphs in a PDF document with a CSV table with second-by-second data as an option for technically oriented participants. Participants could use Excel to investigate the data on their vehicle. A few summary plots and statistics, for example, distribution of second-by-second fuel economy, distribution of vehicle speed, total miles traveled, and average fuel economy, would be provided.

Advance notification package – The advanced notification package for the main study should include, for example, an introductory letter, a study brochure, instructions and passwords for participating in an online recruitment interview, or alternatively for participation in a telephone interview. Enlisting the participation of household adults and their qualified vehicles into the research effort requires a concise and well written introduction that focuses on the benefits of the research, conveys what participation requires (for example, installation of instrumentation on their vehicle and participation in monthly or quarterly online, smartphone, and/or telephone surveys) and offers an incentive to balance out the perceived cost of participation.

As a result of previous testing of advanced notification materials, an oversized colored envelope for the mailing would be used so that it stands out among regular mail. This results in higher participation rates among the advanced mailed sample. For those households that complete the online recruitment page, their next contact would be receipt of the research materials packet by mail.

A variety of topics are candidates for inclusion in the cover letter and study brochure, such as:

- [The main study sponsor] is conducting a study to see why the fuel economy (miles per gallon) that vehicles get can be different from the City/Highway/Combined MPG values that are displayed on new vehicles.
- We all want the cars and trucks that we drive to have better fuel economy. We want to find ways to improve the fuel economy of the cars and trucks that are driven in the United States. To find better ways, we need to begin by finding out what affects the fuel economy on today’s vehicles and what driving conditions, such as road characteristics and weather, our vehicles must operate in.
- We need cars and trucks with 1996 and newer model years that are being actively driven.
- We are looking for about 200[28] people and various types and manufacturers of vehicles all over the United States to participate in the study.
- Participants would be randomly selected.

[28] The number of vehicles in the sample will be selected by the main study sponsor.

- We are interested only in personal vehicles. No company vehicles.
- We are offering incentives to participants to be part of the study.
- We would mail participants a small datalogger that they can plug into a connector located below their dash. We believe that most vehicle owners would be able to follow the written instructions to install the datalogger. Installation assistance would also be available on-line, by telephone, and in person as needed.
- The datalogger measures engine operation, vehicle operation, and vehicle location using GPS.
- Data would be wirelessly transmitted to us for analysis. If requested, information identifying specific vehicles would be removed from the database before analysis, such that there would be no ability to identify specific driving from specific vehicles.
- The datalogger would stay on the vehicle for one year.
- Participants would be able to contact us during the year with questions.
- After the participant installs the datalogger, the participant should just use the vehicle as he normally does. The participant does not need to do anything with the datalogger, such as entering information, after it has been installed.
- We may occasionally contact the participant with requests to check the datalogger's operation.
- The datalogger is a passive device and cannot harm your vehicle.
- The datalogger does not measure the emissions of your vehicle.
- At the end of the year, the participant would disconnect the datalogger and return it to us in packaging and postage that we would mail to the participant at the end of the study.
- There would be a project website that participants can use to see what the project is about, to see how the project is going, to contact us with questions, and to track the incentives that they have earned.
- We can send a copy of the data from your vehicle after the study has concluded if you request it..
- If you agree to participate, you will not have liability for the datalogger if something happens to it. There is no chance that the datalogger can damage your vehicle in any way, which we will warranty.

A draft advanced notification package cover letter is shown in Figure 4-3. The outside and inside of a draft tri-fold study brochure are shown in Figures 4-4 and 4-5. These are sample documents designed for this pilot study report and use the ICCT logo. The documents for the main study would be redesigned using the sponsor's logo and using text reflecting the scope and policies developed for the main study. For example, there should be a statement that there will be no link between the data and the participant and that suggests that this means participants should not have a concern with sharing the data.

Figure 4-3. Draft Advanced Notification Package Cover Letter

icct
THE INTERNATIONAL COUNCIL ON CLEAN TRANSPORTATION

1225 I Street NW
Suite 900
Washington DC 20005
+1 202.534.1600

Website Pin Number – XXXXXXX *(Imported)*
Eligible Vehicle
Year/Make/Model *(Imported)*

JOHN SMITH *(Name & Address Imported)*
12345 MAIN ST
AUSTIN, TX 78746

March 15, 2013 (*Date Imported)*

The International Council on Clean Transportation would like to thank you for considering participation in the important fuel economy study that we discussed with you over the phone on March 8 *(Date Imported)*. The enclosed brochure provides a brief overview of this project. You can also look at the project website at http://www.surveys.nustats.com/ICCT/.

The vehicle described in the gray box in the upper right hand corner of this letter is your vehicle that we are interested in.

There two ways you may sign up to begin participating:

1. Go online to access http://www.surveys.nustats.com/ICCT/
   a. Use the Pin Number listed in the gray box found in the upper right hand corner of this letter.
   b. This will provide access to your previously collected household and vehicle information.
   c. Complete the retrieval questions.
   d. If you have questions, we will provide assistance through the project email notification system or you can call the project hotline at 1-800-XXX-XXXX.

2. If you do not access the website within a week of receiving this advance letter, our interviewer will call you.
   a. The interviewer will ask you the same series of questions asked of those who sign up for participation online.

Once you have answered all of the questions, we will choose the final set of vehicles that we will need in the study. If we choose your vehicle, we will mail you a datalogger with instructions on how to install it on your vehicle.

While we will not sell the data that we gather from your vehicle, we will distribute the data to a variety of vehicle and engine manufactures, the U.S. Environmental Protection Agency, and various other interested parties. Therefore, you need to be comfortable with this – especially considering that Global Positioning System (GPS) data will tell your vehicle's location for the entire one-year data collection period. To protect you, we will not release your identity or the link between you and your vehicle's data.

Your participation is greatly appreciated. With your help we can design and build cars and trucks that get better fuel economy by measuring the detailed engine and vehicle operation of today's vehicles.

Sincerely,

John Smith, Project Manager

Figure 4-4. Outside of Draft Tri-Fold Study Brochure

How do you participate?

Follow these 3 easy steps...

Step 1 **Complete a Vehicle Questionnaire**

Go to **www.surveys.nustats.com/icct** to complete this step online.

You may also call us at **1-800-XXX-XXXX** to participate by phone.

The vehicle information collected in **Step 1** helps ensure that we get input from all types of vehicles.

Step 2 **Install Datalogger**

We will mail you a datalogger to be installed in your vehicle to record vehicle and engine operations for one year.

Step 3 **We Will Call You**

If you do not participate via the website, or by calling our hotline, our highly trained interviewers will call you to enter you into the survey.

Step 4 **Return Datalogger**

At the completion of the study, simply mail the datalogger using the pre-paid box.

Do you want to participate or have more questions?

Visit the survey website:
www.surveys.nustats.com/ICCT

Send an e-mail to:
icctsurvey@nustats.com

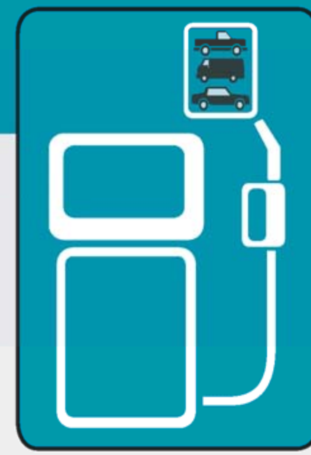
Or call the toll-free survey hotline:
1-800-XXX-XXXX

Survey conducted by:
NuStats

Survey sponsored by:

The study is sponsored and being performed by the International Council on Clean Technologies, a non-profit organization. **icct** is performing a similar study in Europe at the same time as this one in the United States.

Project Contact:
Ryan McCutchan, *Project Manager*
1-800-XXX-XXXX
email: *icctsurvey@nustats.com*



With your help, we can improve fuel economy!

Survey sponsored by:

icct
THE INTERNATIONAL COUNCIL ON CLEAN TRANSPORTATION

WWW.SURVEYS.NUSTATS.COM/ICCT
HOTLINE TOLL-FREE: 1.800.XXX-XXXX

Figure 4-5. Inside of Draft Tri-Fold Study Brochure

About the Study

icct is conducting a study to see why the fuel economy (miles per gallon) that vehicles get can be different from the City/Highway/ Combined MPG values that are displayed on new vehicles.

We all want the cars and trucks that we drive to have better fuel economy. Thus, we want to find ways to improve the fuel economy of the cars and trucks that are driven in the United States. To find better ways, we need to begin by finding out what affects the fuel economy on today's vehicles and what driving conditions, such as road characteristics and weather, our vehicles must operate in.

We need cars and trucks with 1996 and newer model years that are being actively driven. We are looking for 200 participants and various types of manufacturers of vehicles all over the United States to participate in the study. Participants will be randomly selected. The study will focus only on personal vehicles. Company vehicles and heavy duty vehicles are not eligible to for this study. We are offering incentives to participants that complete the study.

Light-Duty Vehicle In-Use Fuel Economy Data Collection

Panelists will not be liable for the datalogger if something happens to it.

- We will mail participants a little datalogger that they can plug into a connector located on their dash.
- Installation instructions will accompany the datalogger.
- Installation assistance will also be available online, by telephone, and in person as needed.
- The datalogger will stay on the vehicle for one year.
- After the participant installs the datalogger, the participant should just use the vehicle as he normally does.
- Data will be wirelessly transmitted to us for analysis.
- At the end of the year, the participant will disconnect the datalogger and return it to us in packaging and postage that we provide.

The datalogger is a passive device and cannot harm your vehicle. If you agree to participate, you will not have liability for the datalogger if something happens to it. We may occasionally contact the participant with requests to check the datalogger to verify activity. Since we will have data that will show where you have driven, you need to be comfortable with us having that knowledge.

Why participate?

Because...

1. **You are important.**
   Your vehicle was picked to represent vehicles like yours across the United States.
2. **We appreciate your time.**
   Your participation will assist us in future planning that will benefit the fuel economies of future vehicles by assessing engine and vehicle operations.

Incentives

1. **Monetary Incentive of $100!**
2. **$100 Worth of Gift Cards**
3. **One Year Triple-A (AAA) Membership**
4. **One Year Vehicle Data Report (detailed data over the course of one year that can be used to assess personal driving habits and patterns)**

Project website – To achieve the main study's communication and survey participant collaboration needs, it would be useful to develop a website to provide information about the survey and to deliver an online recruitment and retrieval processes for basic data. A participant's Personal Identification Number (PIN) could be provided to and be required from participants submitting information through the website. The website would also add legitimacy to the study and serve as a point of engagement for participants who have opted for web-based communication. Based on our experience with using similar websites for travel behavior surveys, which carry a similarly high burden for participants, the website forum would have a positive impact on survey cooperation and response rates throughout the study. The website should mirror the look and feel of the printed materials that would be developed.

A draft of a sample fuel economy main study website homepage is shown in Figure 4-6.

The reader can go to http://www.surveys.nustats.com/ICCT/ to examine the sample website. For this pilot project the website has limited operation. The final study website would include important features to help ensure that information entered by the participant candidate would have few errors.

The main study's website would provide the following information to members of the general public and survey participants:

- Study information for participants – Topics to provide information about the study for participants would include research purpose and benefits, information about the study sponsor, survey/participant privacy, and information about participation.

- FAQs about the study – A dynamic FAQ-style approach would be used to answer common questions about the study. The frequently asked questions would be database driven and can easily be modified and added to as new questions or issues arise during the course of the study.

- Contact method for participants and the public – The website would provide a way for participants and others to contact the study team in a formal manner, whereby all messages are logged to a central database for monitoring and tracking. The public can submit questions on a variety of categories to help direct the messages to specific persons or groups within the study team (for example, how to install the dataloggers, how the data would be used, web technical support, etc.).

- Online recruitment – The website would have tools that allow respondents to participate in the study by answering a series of recruitment questions using a simple survey style web interface.

Figure 4-6. Draft Main Study Fuel Economy Website Homepage

icct

THE INTERNATIONAL COUNCIL ON CLEAN TRANSPORTATION

The International Council on Clean Transportation (ICCT) is conducting a pilot study to collect second-by-second operation data on a randomly selected set of 1996 and newer personal vehicles in the United States. The focus of the study will be to measure fuel economy (miles per gallon) each second as vehicles are driven and, at the same time, to measure the major factors (like road grade and air-conditioning use) that influence fuel economy.

Participants in the study will be mailed a datalogger that they can easily plug into an existing connector located on the vehicle dash. Each device will be accompanied with instructions on how to install the datalogger. Assistance will be available on-line through this website and by phone. In-person assistance will also be available for individuals if required.

The datalogger is a little electronic box that retrieves and records vehicle and engine data, as well as Global Positioning System data. The datalogger is a passive device that will not harm vehicles. Once the device is installed, the participant will use their vehicle normally and will not be required to enter information or interact with the datalogger in any way. An automatic process will wirelessly transmit data to the ICCT for analysis. The dataloggers will collect data for one year. Participants will receive incentives for their participation. Participants may be contacted occasionally if the datalogger is inactive for long periods of time. All participants will receive the following incentives for their participation:

- Monetary Incentive of $100
- $100 worth of Gift Cards
- 1 year AAA (American Automobile Association) membership with Roadside Assistance
- 1 year vehicle data report - detailed data over the course of one year that can be used to assess personal driving habits and patterns and vehicle and engine operation

The data collected in this study will assist the ICCT in answering the following questions:

- What factors affect vehicle fuel economy and by how much?
- What driver behavior factors influence in-use fuel economy and by how much?
- How do weather and road grade (incline) affect fuel economy?
- What are the ranges and distributions of fuel economy influencing factors that U.S. vehicles are exposed to?
- How does in-use fuel economy deviate from the new vehicle fuel economy and environment label values?

ICCT is an independent non-profit organization that focuses on how to improve the environmental performance and energy efficiency of road, marine, and air transportation, in order to benefit the public health and mitigate climate change. Your participation is greatly appreciated. With your help we can design and build cars and trucks that get better fuel economy by measuring the detailed engine and vehicle operation of today's vehicles.

Start Survey

Thank you in advance for your time and help with this important survey!

- Data submission – A web-based retrieval instrument would enable respondents to provide their basic data online. This could be especially useful for basic vehicle data submitted by vehicle owners.

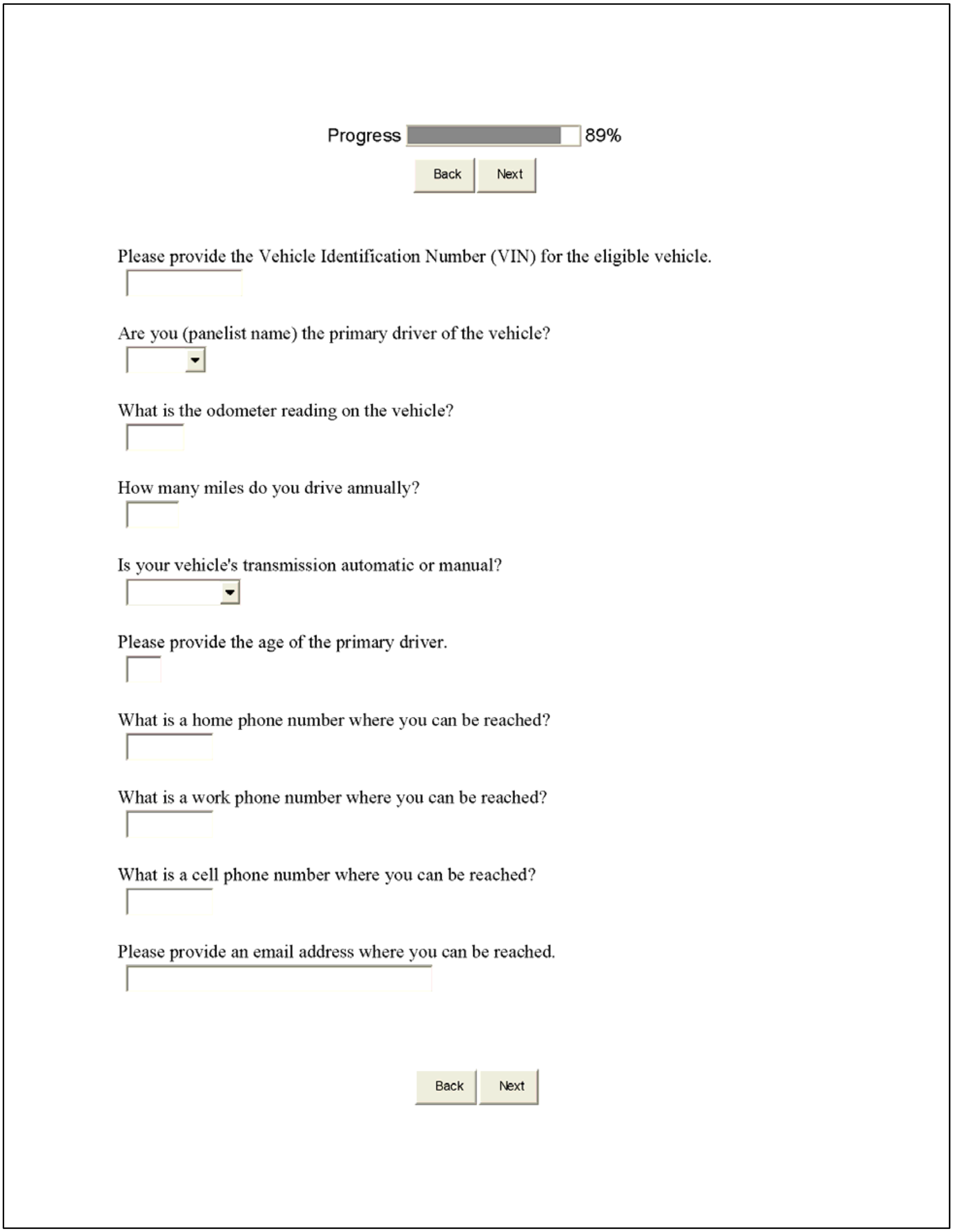
- Discussion board – A survey or discussion board venue would be used for periodically engaging participants in the study to maintain their interest and retain them as participants. This would include a tool for tracking their earned incentives throughout the study.

- Password protection – Most pages on the public website would not be password protected. However, access to the online versions of the recruitment, data retrieval, scripts, and periodic surveys would require a PIN or other login information. The site's pages would be designed with the user in mind to make the access to all project information, documentation, and data files simple and user-friendly.

Figure 4-7 shows a draft online recruitment page that would be used to support online recruitment described by the top rectangle in the second column of Figure 4-2. Figure 4-8 shows a draft recruitment sign-off page. The final study website recruitment pages would include important features to help ensure that information entered by the participant candidate would have few errors. These features would include VIN check digit checking with request for re-entry if the entered VIN had an error and opportunity to change the name of the primary driver.

Telephone recruitment tools – As mentioned in Section 4.2, only about 20% of the households that receive the advanced notification package are expected to respond by completing the website recruitment page. About two weeks following the mailing, the remaining 80% of the targeted households would be contacted using telephone recruitment calls. Recruitment interviewers would attempt to establish a rapport with the household contact, answer basic questions about the study, and efficiently and effectively secure household participation. The interviews would be accomplished by the telephone interviewer filling out the online recruitment page that the targeted household would have filled out had it responded online. A series of "hot buttons" would be available to the interviewer to guide the interview through the recruitment webpage to ensure collection of all critical data elements, to describe the project to the interviewee, and to answer questions that might arise.

Figure 4-7. Draft Online Recruitment Page


Progress 89%

Back Next

Please provide the Vehicle Identification Number (VIN) for the eligible vehicle.

Are you (panelist name) the primary driver of the vehicle?

What is the odometer reading on the vehicle?

How many miles do you drive annually?

Is your vehicle's transmission automatic or manual?

Please provide the age of the primary driver.

What is a home phone number where you can be reached?

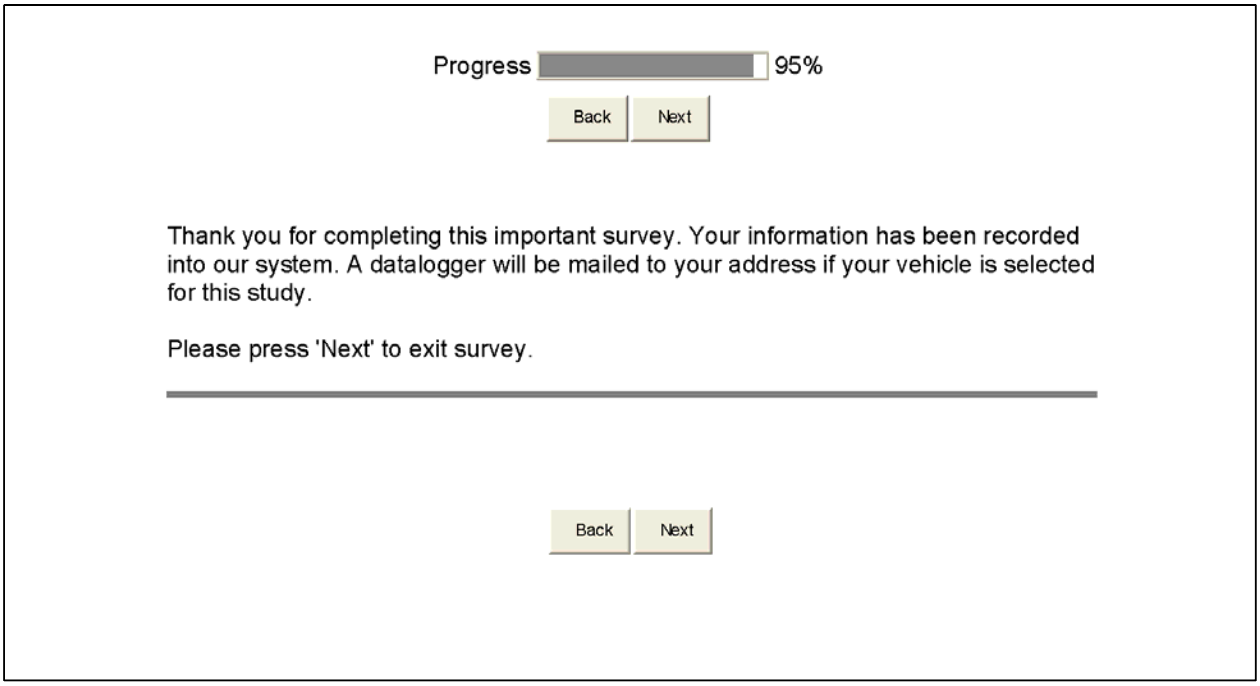
What is a work phone number where you can be reached?

What is a cell phone number where you can be reached?

Please provide an email address where you can be reached.

Back Next

Figure 4-8. Draft Online Recruitment Sign-Off Page



Regardless of whether a household contact agrees to participate via the online survey or the telephone interview, they would have completed a short recruitment screening interview to confirm eligibility and to document demographic characteristics.

At the conclusion of the recruitment interview, the home address, mailing address, and/or email address would be confirmed or obtained, and the conditions for payment of the incentives would be reiterated. Experience has shown that consistent confirmation of how and when an incentive is earned increases the effectiveness of this participation technique, while ensuring that the budget for the incentives yields the desired return in terms of increased participation levels.

Assistance with dataloggers – Within one week following recruitment by telephone or by online website, each participant’s vehicle and demographic information would be used to customize participation packets for each vehicle owner. The packet would include a cover letter, a datalogger, datalogger installation instructions, a reminder of the study participation time period, and a participant booklet among other items. The assembled packets would be sent to the recruited households by Federal Express with insurance for the value of the datalogger. During this initial phase, the vehicle owner would automatically register as a participant when they install the instrument on their vehicle and the datalogger begins wireless data transmission (if this option is selected for datalogging).

Because of the nature of OBDII dataloggers, most participants should be able to install the datalogger on the vehicle. The installation instructions in the participation packet would provide guidance for performing the installation. In addition, installation instructions would also be available on the project website in the event that the participant has misplaced the installation instructions. For those participants that require additional assistance with installing the datalogger, over-the-phone support would be available through a telephone number provided in the participation packet. Finally, for those participants with the desire to participate but who may not have the skills, time, or desire to install the datalogger on his vehicle, an installation service would be available to assist with the installation. This service would contact the participant, make an appointment to install the datalogger, go to the vehicle, and perform the datalogger installation at the participant's convenience and at no cost to the participant.

At the end of the one year data collection period, the datalogger would need to be returned to the project team. At this time, the participant would receive pre-paid return Federal Express packaging materials. Just as with datalogger installation, datalogger retrieval instructions would be provided with the packaging materials. Datalogger retrieval options would also include online support, telephone support, or in-person support by a technician.

Participant management tools – The length of time between the start (vehicle instrumentation) and end (datalogger removal) phases of the study of up to one year suggests that at least four responding contacts be made during the study. The focus of these contacts should be on confirming and updating owner information, including changes in vehicle ownership and changes in driving or environmental conditions. These "maintenance contacts" should be short and simple and be administered by mail, with web and telephone options according to the participant's preference. The responses would be tracked so that a lack of online or mail response would result in a telephone contact.

Participation by owners of sampled vehicles is critically important to the success of this project. The advance letter for participating vehicle owners and the introductory script for recruitment must fully disclose the level of commitment required for participation; and it must be done in a very inviting manner so that participation is viewed as important to the community and relevant to their personal mobility. The challenge of recruiting and retaining participants involves not only motivating them to participate, but also not "over educating" them on the transportation issues, which can inappropriately bias responses.

After a candidate initially accepts participation in a study, a principle problem of panel research is attrition. The recommended design would be structured to minimize that attrition by several activities. Targeted incentive payments are cost effective methods of minimizing attrition. Therefore, participants should receive an incentive payment in return for each interim contact opportunity in which they participate. Finally, in the event that a sampled vehicle owner or their eligible vehicle is no longer able to participate in the study, protocols would be set at the design phase of the study for a replacement vehicle. These protocols would define the criteria for recruiting a replacement vehicle to meet the study requirements.

4.4 Validation of Vehicle Recruitment Methodology

The vehicle recruitment methodology can be validated using two different activities. The first activity is cognitive testing which occurs on draft recruitment materials using a small group of people to evaluate the understanding of those materials. The second is a shakedown process that would occur during the beginning of the main study as initial candidates are slowly recruited for the study. During this shakedown period, recruiting methodology can be evaluated and modified based on the initial findings of actual participant candidates and participants.

4.4.1 Cognitive Testing

Cognitive testing can be used to evaluate the effectiveness of draft recruiting materials. This kind of testing involves selecting people who have no prior knowledge of the project to work through the materials just as participant candidates would use the materials. After that testing, the people are interviewed to determine whether they understood the concepts covered by the recruiting materials. If there was a misunderstanding or a concept that was unclear, then the draft recruiting materials can be modified to remove the problem. Four different recruiting materials would benefit from cognitive testing.

Advance notification package cover letter – The advance notification cover letter, a draft of which is shown in Figure 4-3, is used to re-acquaint a person who expressed willingness to be a participant in the main study during their initial interview in the household travel survey. The major purpose of the cover letter is to provide more details about the project to the candidate and to encourage them to register as an official candidate for participation online or through a telephone interview. Cognitive testing would be performed by having people unfamiliar with the project read a draft cover letter and then be interviewed by the cognitive tester.

Advance notification brochure – The advance notification package would also contain a tri-fold brochure that gives additional details about the main study. The small group of cognitive testing people would also be asked to examine the brochure in the presence of the cognitive examiners. A conversation between each person and the examiner would determine if the person understands the brochure and would help identify questions that a participant candidate might have. If some of the questions are repeatedly asked by people, then those questions may need to be included either in the project website or brochure to add clarity.

Project website – The advance notification cover letter would direct participant candidates to the project website. The website would contain a splash page and a recruitment page, at a minimum. The group of people undergoing cognitive testing would be asked to sit down at computers, go to the study website, and register on the project website for participation. They would be asked about the content of the splash page and about any problems or questions they might have about registering for recruitment. After that cognitive testing is completed, modifications can be made to the project website for its improvement.

Telephone recruitment hot buttons – To cover recruitment of candidates who prefer telephone recruitment over online recruitment, a group of people unfamiliar with the project would undergo cognitive testing using the telephone recruitment technique. In this situation, the people would be interviewed one-on-one and in person by an examiner who reads the online questions to them as if they were speaking on the telephone. For telephone recruitment, interviewers would have a set of hot buttons which only they can see on the online recruitment page to provide guidance to the interviewer and to answer questions that a participant candidate might have. The effectiveness and the understanding of the content of the text and hot buttons would be tested during cognitive testing. Any modifications that need to be made to the hot buttons text to improve understanding or clarity would be made before recruiting for the main study begins.

4.4.2 Development and Adjustments During Main Study Shakedown

Some characteristics of the recruiting methodology are difficult to develop and adjust using just cognitive testing. For those characteristics, adjustments of the recruiting methodology can be made during the initial phases of the main study which we call the shakedown phase. During the shakedown phase, the rate of participant recruitment may be kept relatively low to allow time for adjustments to be made.

Incentive investigation – For a national effort of one-year duration, incentives need to be offered to convince a sufficiently large percentage of candidates to participate. Many different types and sizes of incentives can be designed. However, which of these designs work adequately well can probably be determined only by trying them on participant candidates. Some draft incentive packages were presented in Section 4.1. During the shakedown phase, these draft incentive packages, as well as others that may be thought of, can be tested on initial participant candidates to determine which may be most effective. Following this initial incentive testing during the shakedown phase, a single incentive package would probably need to be settled upon. However, in some circumstances, the incentive may need to be negotiated. For example, for vehicles that are rare in the fleet, higher incentives may be offered so that all bins in the stratification structure may be filled.

Feedback and frequently asked questions – The questions and comments from the first participant candidates who are communicated with – either verbally on the telephone or through e-mail – would reveal common questions and misunderstandings that participant candidates may have. By recording these comments, questions, and suggestions, the recruitment tools can be improved so that future participant candidates would be better informed early in the recruitment process. Some of the frequently asked questions, for example, may be so common that they would need to be put in the FAQ list on the project website.

Evaluation of efficiency rates – The flow diagram for recruitment shown in Figure 4-2 used assumed values for efficiency rates at different points in the recruitment process. To a degree, these rates are based on little prior experience. During the shakedown phase, the dispositions of early participation candidates, with regard to their flow through the process would provide more concrete and realistic values for the actual efficiency rates that would be observed during the main study. As more and more participant candidates are recruited and become part of the participant pool, the updated efficiency rates can be used to refine the estimates of the numbers of vehicles and owners that would be needed to complete the main study.

5.0 Datalogger Design

5.1 Objectives and Approach

All 1996 and newer light-duty gasoline-powered vehicles and 1998 and newer light-duty diesel-powered vehicles manufactured for sale in the U.S. are equipped with second-generation on-board diagnostic systems, generally referred to as OBDII. These OBDII systems provide SAE-standardized information as well as manufacturer-specific, or enhanced, information that is available using special request and decoding information available from the vehicle manufacturers. One objective of this pilot study was to procure or develop a system that collects and records this OBDII data in order to gather vehicle operating information that could be used to calculate in-use second-by-second fuel economy estimates as well as various operating information such as vehicle speed, acceleration, location, and engine operating conditions. A system was sought for use in this study that would record the vehicle's OBDII data and turn on and off automatically without user input. For data resolution reasons, some parameters must be collected at rates up to 2 Hz, although other parameters may be collected at a lower rate. Collection of SAE-standard and some manufacturer-specific (enhanced) parameters will be required.

Table 5-1 was developed based on requirements provided in ICCT's September 5, 2012, Request for Proposals and lists the initial specific requirements for the datalogger to be sought for this study, as well as ERG's intended approach for obtaining the information. This information and approach formed the basis for ERG's datalogger research.

Fuel Type – Due to each vehicle's ability to automatically adjust air/fuel ratio based on exhaust oxygen content, determination of fuel type from the OBDII datastream can be challenging in a large vehicle study. ERG investigated using fuel trim and oxygen (or lambda) sensor ratio data along with mass air flow rates to determine feasibility of quantifying ethanol content. However, it was determined the most practical approach would be to collect regional fuel ethanol content data in each area in which the study is being conducted. As a verification of regional data, it may be possible to request participants to occasionally use specific brands of oxygenated fuels with known ethanol content (purchases at certain gas stations could be verified using GPS data or fuel receipts). The operating data obtained for that tank of fuel could then be used to "calibrate" the effect of fuel type on fuel economy (i.e., adjust the stoichiometric air/fuel ratio for the actual known fuel being used).

Table 5-1. Summary of Datalogger Requirements

Data Requirement	Approach Description
Date/ time, 1 Hz	Date/time will be required for each trip (engine on/off episode).
Vehicle speed, 2 Hz	Vehicle speed is a standard SAE J1979 PID, and will also be available from the logger's GPS. At least one of these two parameters will be acquired on a 2 Hz basis (the other may be 1 Hz), in order to allow acceleration calculations.
Vehicle acceleration, 2 Hz	A datalogger with an internal 3-axis accelerometer with 2 Hz acquisition capability will be sought. Acceleration may also be computed from OBD or GPS speed.
Distance traveled, 1 Hz	Distance traveled is to be calculated from vehicle speed (OBDII PID 0D) or GPS data, whichever is used for vehicle speed.
Fuel rate, 2Hz	Data which can be used to calculate fuel consumption will be collected on a 2 Hz basis. Several methods were evaluated and are described later in this report.
Fuel type, 1Hz	The ability to determine fuel type (ethanol content of fuel) was desired. The recommended approach for collecting this information is described in the Fuel Type section which follows.
Intake air temp, 1 Hz	Both ambient air temperature (PID 46) and intake air temperature (PID 0F) are standard SAE J1979 PIDs which may be requested on a 1 Hz basis.
Engine speed, 1 Hz	Engine RPM (PID 0C) is a standard SAE J1979 PID that may be requested on a 1 Hz basis.
Engine load, 1 Hz	Absolute load (PID 43), calculated load (PID 04), and throttle position (PIDs 11, 45) are standard SAE J1979 PIDs which may be requested on a 1 Hz basis.
Altitude, 1 Hz	Barometric pressure (PID 33) is a standard SAE J1979 PID and may be requested from the OBDII-port, and altitude will also be collected (if available) from the GPS data on a 1 Hz basis. If higher accuracy is needed, vehicle altitude obtained from an overlay of vehicle GPS coordinates onto GIS maps could be developed and would likely more accurate than GPS altitude.
Road grade, 2 Hz	Although not specified as a datalogger requirement, road grade is important since it affects engine load. Road grade can be estimated from GIS altitude differences, a barometric altimeter, or possibly calculated from 3-axis accelerometer data. The acquisition rate should be equivalent with speed and acceleration acquisition rates (2 Hz).
Location, 1 Hz	Geographic location will be collected from the GPS data on a 1 Hz basis.
Climate control and A/C compressor, 1 Hz	Collection of cabin climate control and air conditioning compressor on/off status was specified, and the approach for collecting this information is described in the "Climate Control" section, which follows.
Hybrid battery state of charge, 1 Hz	Collection of OEM Enhanced PIDs will likely be required for acquiring battery state of charge for hybrids. "Hybrid battery pack remaining life" (PID 5B) may be available on some vehicles, and may yield sufficient information for calculate power usage during vehicle operation.
IC engine on/off status, 1 Hz	Several standard SAE J1979 PIDs may be used to determine internal combustion (IC) engine on/off status, such as mass air flow rate (PID 10), manifold absolute pressure (PID 0B), or RPM (PID 0C).
Data Storage	The logger was specified to be able to store a full year's worth of data and / or periodically transmit the data wirelessly. The approach for this is described in the section entitled "Data Handling and Storage".

Climate Control – Air conditioning compressor on/off status affects fuel economy and is therefore important to identify. Generally, the status of a component not directly related to the powertrain is not available as a standard SAE J1979 parameter. One approach for acquiring this information is through collection of enhanced (OEM-specific) data for specific vehicle controllers, although these queries will vary by manufacturer and sometimes model year. This will add cost to the dataloggers and will have some fleet coverage limitations. Alternatively, A/C compressor status may be determined by comparing cabin temperature (as measured by an external thermocouple linked to the datalogger) with ambient temperature, or it may be possible to develop an algorithm using engine load, throttle position, and engine RPM (all SAE J1979 standard parameters) to determine when the air conditioning compressor cycles on and off. It might also be possible to use the output from a voltage spike detector to identify when the A/C compressor cycles on and off, although the strength of this signal could vary from vehicle to vehicle and will be obscured by the vehicle's voltage regulation and voltage changes due to intermittent use of other accessories such as vehicle lights. The feasibility of these alternative strategies (thermocouple measurements, load/throttle position/RPM evaluation, and voltage spike analysis) was beyond the scope of this pilot study but could be explored in the future as needed.

Data Transmission and Storage – The amount of data collected, and therefore the memory required, over the study will be dependent on the final list of OBDII variables available for each vehicle (i.e., number of variables and number of bytes per variable), the type of logger used, the number and type of additional non-OBDII variables collected (such as GPS, logger/cabin temperature, barometric altimeter, and accelerometer data), the acquisition rate by variable, the type of data file used to store the data, and the amount of time each vehicle is driven. A preliminary assessment performed by ERG shows a datalogger collecting 30 channels of ASCII data on a 2-hz basis (OBDII parameters with GPS), operating for 24-hours per week (approximately 3.5 hours/ day) for 52 weeks per year would collect approximately 1.3 GB of data.

The three options for handling data include storing the data locally and periodically transmitting data packets via a cellular modem, local storage and transmitting the data via Wi-Fi, or relying exclusively on on-board storage (internal or SD card). Each of these options is discussed in Section 5.3.3. For both the cellular and the Wi-Fi options, data would be stored locally on the datalogger until after the data was broadcast and verified. This would most likely be accomplished through the use of rolling memory in which records are not overwritten until the memory allocation is full, and then only the oldest records are overwritten. This would help ensure data is transferred and verified prior to any records being overwritten.

5.2 Fuel Economy Estimates

Before describing the market research conducted to identify dataloggers for use in this study, an overview of some methods of calculating fuel economy and the conditions under which those methods would be used is now provided.

Our objective in this study was to obtain acceptably accurate instantaneous (i.e., second-by-second) fuel economy estimates from a broad variety of vehicles under a diverse range of operating conditions using standardized SAE J1979 PIDs. However, there are some scenarios in which the use of the SAE J1979 PIDs might not provide suitable results, since the availability of specific generic "live datastream" PIDs varies among vehicle types and operating conditions. The vehicle types and operating conditions expected to be encountered are described below, along with our recommended approach for estimating fuel consumption in each of these scenarios.

5.2.1 Vehicle Types

Gasoline Vehicles That Broadcast Mass Air Flow – Many gasoline-powered vehicles directly report an estimate of the mass of air entering the engine as measured by the engine's mass air flow sensor. These can include port fuel injected vehicles, gasoline direct injection vehicles, and hybrids. For these vehicles, the gasoline combustion equation and the reported mass of air provided to the engine can be used to calculate the amount of fuel required for stoichiometric engine operation. Deviations from stoichiometric operation can be calculated using the ratio of actual combustion to theoretical stoichiometric combustion (lambda), which is reported as a standard SAE J1979 PID for vehicles with wide-band oxygen sensors. The following equation may therefore be used to calculate such a vehicle's instantaneous fuel economy:

$$\text{Fuel Economy (distance per fuel volume)} = k_1 * \frac{\text{Speed} * \lambda * \text{AFR}_{\text{stoich}}}{\text{Mass Air Flow}}$$

In the above equation, λ represents the adjustment for non-stoichiometric operation, and k is a constant that accounts for various unit conversions and an estimated density of the fuel. The mass of air required for stoichiometric combustion will vary based on the ethanol content of the fuel. The following equation, with similar variable definitions, may be used to calculate fuel used on a time-basis:

$$\text{Fuel Consumption (volume per time)} = \frac{k_2 * \text{Mass Air Flow}}{\lambda * \text{AFR}_{\text{stoich}}}$$

Not all vehicles are manufactured with wide-band oxygen sensors. For vehicles without wide-band oxygen sensors, lambda is not available as a standard SAE J1979 parameter. Instead, a voltage output from a narrow-band oxygen sensor is typically available. As opposed to the wide-band oxygen sensor, which provides a moderately linear output signal over a relatively wide operating range, the narrow-band oxygen sensor functions a bit like a binary switch (rich or lean). Because small changes in amount of exhaust gas oxygen content radically change the output voltage, voltage output from a narrow-band sensor cannot be used to accurately quantify deviation from stoichiometric, but instead only indicates whether a vehicle is operating at stoichiometric, rich, or lean conditions. Therefore, for these vehicles, overall average fuel economy estimates can be determined using standard SAE J1979 PIDs (since these vehicles generally target stoichiometric operation), but accurate instantaneous fuel economy estimates using narrow-band oxygen sensor data can be problematic. For narrow-band oxygen sensor vehicles, it may be possible to use calculated load (standard PID 04) along with mass air flow, to calculate fuel rate during non-stoichiometric operation, or alternatively, the use of OEM-specific (enhanced) fuel injector rate data may provide acceptably accurate instantaneous fuel economy estimates. If fuel injector rate data is not available as an OEM-specific parameter, it may be possible to use fuel injector pulse width (this would also be an OEM-specific parameter) data to estimate instantaneous fuel consumption. The relationship between fuel injector pulse width and fuel rate (calculated with mass air flow) observed during instances of stoichiometric operation could be used to correlate fuel injector pulse width with fuel rate for non-stoichiometric operation. For some late model vehicles, engine fuel rate (SAE J1979 standard PID 5E) may also be available to directly determine fuel economy, but the accuracy of this PID and prevalence in the on-road U.S. fleet is unknown. Results from analysis of vehicles with both wide-band and narrow-band oxygen sensors are provided in the Datalogger Validation section of this report, Section 5.5.

Gasoline Vehicles That Do Not Broadcast Mass Air Flow – Many on-road vehicles provide a mass air flow signal (see Section 5.2.2). However, a number of vehicles (Chrysler, Honda and certain vehicles from other manufacturers) use the absolute pressure measured in the intake manifold to estimate the mass of air entering the engine using models involving the volumetric efficiency and displacement of the engine. This type of engine management is referred to as the Speed-Density method, and is based on the ideal gas law but with a volumetric efficiency factor to account for the volume variable in the ideal gas law.

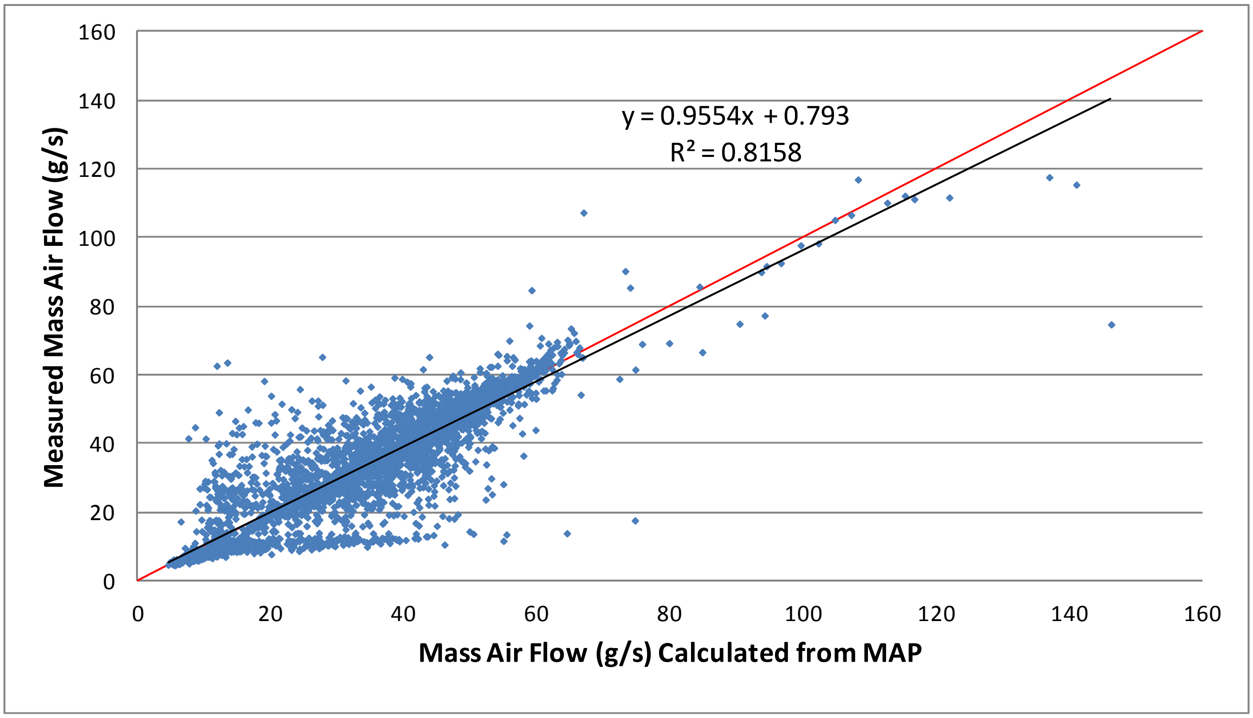
$$\text{MAF} = \frac{\text{MAP} * \text{Displacement} * \text{RPM} * \text{\% Volumetric Efficiency}}{k_3 * R * \text{Temperature}}$$

In the above equation, R is the ideal gas constant and % Volumetric Efficiency is a function of manifold absolute pressure and engine speed which is calculated using look-up tables stored in a vehicle's engine control unit (ECU). Using the appropriate value for volumetric efficiency (based on engine speed and load), the vehicle's ECU can then calculate an estimated mass of air entering the engine at that point in time, and determine the amount of fuel necessary for optimal combustion.

However, this presents a problem when trying to estimate fuel economy using standard SAE J1979 OBDII data. While it is possible to assume an average volumetric efficiency for an engine, this estimate will not accurately represent instantaneous volumetric efficiency, since values for volumetric efficiency vary significantly based on engine load and speed, and the volumetric efficiency "maps" vary among engine types. For individual vehicles (engine and model year), it may be possible to obtain the factory volumetric efficiency look-up tables in order to determine mass air flow, but it would be expensive and difficult for a broad vehicle study such as this. It may also be possible to estimate volumetric efficiency table look-up values by parameterizing "average" values into equations that predict approximate volumetric efficiency based on engine speed and load, but again these equations will be engine-type dependent and will not likely provide needed accuracy over a wide range of operation.

ERG performed a preliminary feasibility assessment of the accuracy of calculating mass air flow from manifold absolute pressure using general speed-density equations and OBD data from a 2006 Ford Freestar with a 3.9L normally-aspirated V6 engine (the OBD system for this vehicle broadcasted both MAP and MAF data). After developing general equations to estimate mass air flow from manifold absolute pressure and engine speed based on general speed-density information and a "typical" speed-density table downloaded from the Internet, ERG estimated mass air flow from the Freestar's MAP and RPM data collected during a 90-minute drive. A scatter plot of the calculated values vs. the measured values is shown in Figure 5-1, with the 1:1 line shown in red. ERG did not attempt to refine this methodology to improve the correlation, although future proposed analysis for MAP to MAF conversions is described in Section 5.6.1 (Evaluate MAP-to-MAF Conversion Calculations), and analysis to calculate fuel rate from MAP and narrow band-equipped vehicles is proposed in Section 5.6.3 (Calculate Fuel Flow Rate for Manifold Air Pressure / Narrow-Band O2 Sensor Gasoline Vehicles).

Figure 5-1. Preliminary Assessment of Calculating Mass Air Flow from Manifold Absolute Pressure



Use of OEM-specific queries (enhanced PIDs) of fuel injector rate is another alternative for determining instantaneous fuel economy estimates for vehicles that do not provide mass air flow as a standard SAE J1979 parameter. If fuel injector rate is not available as an OEM-specific query, it may be possible to use fuel injector pulse width (this would also be an OEM-specific query) in order to estimate instantaneous fuel consumption. However, for MAP-only vehicles, the relationship between fuel injector pulse width and fuel injector volume could be difficult to obtain without fuel injector calibration curves. We envision that research will be required, by vehicle manufacturer, in order to convert each manufacturer's relevant enhanced data into common fuel rate information that can be used in the study. We do not envision standard "fuel rate" (mL/s or similar) will generally be directly broadcast as an enhanced PID, at least on older vehicles. In addition, as shown in Section 5.5.2 (Standard SAE J1979 vs. OEM-enhanced Validation), ERG identified some potential issues associated with the accuracy of fuel economy estimates based on fuel injector volume (an enhanced PID). As described in Section 5.6.6., more investigation is needed to better understand the limitations of fuel economy estimates based on enhanced PID data.

Diesel Vehicles – Because of the broad variety of diesel engine sensors and air/fuel management techniques, and also the wide range of air/fuel ratios over which diesel engines operate, methods to calculate fuel consumption of a diesel engine differ from those to calculate fuel consumption from a gasoline (stoichiometric) engine. OEM-specific queries of fuel injector rate may provide acceptably accurate instantaneous fuel economy estimates for diesel-powered vehicles, or strategies employing fuel rates based on instantaneous engine loads (standard SAE J1979 data) may be used, but these methods can require engine-specific datalogger calibrations that might be challenging over a fleet-wide vehicle study. As stated previously, ERG identified some potential issues associated with the accuracy of fuel economy estimates based on fuel injector volume (an enhanced PID). More work is needed to evaluate methods to calculate fuel consumption from diesel vehicles, as described in Sections 5.6.4 (Analyze Light-Duty Diesel Vehicle Exhaust Data and OBD Data) and 5.6.6 (Perform additional evaluation of enhanced PID data).

Hybrid (non-plug-in) Vehicles – One objective of this study is to measure fuel economy for non-plug-in hybrid vehicles. The strategy to determine the instantaneous fuel economy is the same as described above, and OEM-specific parameters are recommended for collection of hybrid battery state of charge data. This information may be required in determining the overall energy (fuel and electrical) consumed during any particular trip.

5.2.2 Prevalence of Mass Air Flow Vehicles in the U.S. Vehicle Fleet

The data obtained during testing of vehicles in the Kansas City Light-Duty Vehicle Study[29] can be used to estimate the fraction of the OBD-equipped fleet that provides mass air flow data. Because that study was performed in the 2005 timeframe, only model year 2005 and older vehicles were included in the study. Accordingly, the Kansas City data can be used to determine the prevalence of OBD mass air flow broadcasting only for 1996 to 2005 model year vehicles.

ERG examined OBD data from the Kansas City Study and confirmed that OBD data had been logged for 343 vehicles. The OBD data for those vehicles was examined to estimate the fraction of the OBD-equipped fleet that provides mass air flow data. The Kansas City Study results were evaluated by model year and by vehicle make to identify trends in MAF prevalence. Table 5-2 presents results of this analysis by vehicle make. As can be seen in this table, a slightly higher number of vehicles broadcast MAF data than those that did not (53% of the vehicles broadcast MAF, compared to 47% that did not). Chrysler-family vehicles (Chrysler, Dodge,

[29] S. Kishan, A.D. Burnette, S.W. Fincher, M.A. Sabisch, W. Crews, R. Snow, M. Zmud, R. Santos, S. Bricka, E. Fujita, D. Campbell, P. Arnott, “Kansas City PM Characterization Study, Final Report,” prepared for U.S. Environmental Protection Agency, prepared by Eastern Research Group, BKI, NuStats, Desert Research Institute, October 27, 2006, http://www.epa.gov/oms/emission-factors-research/420r08009.pdf.

Honda, Jeep, and Plymouth) and Honda vehicles were primarily non-MAF. A few General Motors makes (Geo, Saturn, Pontiac, and GMC), Acura, and Toyota were found to have some non-MAF vehicles. Vehicles of the remaining manufacturers seem to primarily broadcast MAF.

Table 5-3 presents the prevalence of MAF vs. non-MAF data by vehicle model year, as seen in the Kansas City data. As can be seen in this table, no clear model year trend is evident.

To ensure the vehicle make profile from the vehicles tested in the Kansas City study was similar to the vehicle make profile of the on-road U.S. fleet, ERG compared the vehicle make percentages of the Kansas City Study OBD vehicles included in this analysis with the by-make percentages from Maryland registration data. Results of that comparison are provided in Table 5-4. In general, the by-make percentages from the Kansas City data and the Maryland registration data were similar enough that no reweighting was deemed necessary for this evaluation.

Table 5-2. MAF vs. non-MAF Vehicles from Kansas City Data, by Make

Make[30]	MAF Data Present	MAF Data Missing
ACURA	1	1
BUICK	9	1
CHEVROLET	27	4
CHRYSLER	0	13
DODGE	0	31
FORD	48	3
GEO	0	1
GMC	2	2
HONDA	0	57
HYUNDAI	2	0
INFINITI	1	0
ISUZU	4	1
JEEP	0	10
KIA	8	0
MAZDA	7	0
MERCURY	6	0
MISTUBISHI	3	0
NISSAN	14	0
OLDSMOBILE	4	0
PLYMOUTH	0	7
PONTIAC	1	4
SATURN	1	11
SUBARU	3	0
TOYOTA	38	14
VOLKSWAGEN	1	0
VOLVO	3	0
Total	**183**	**160**

Table 5-3. MAF vs. non-MAF Vehicles from Kansas City Study Data by Model Year

Vehicle Model Year	MAFs Present	MAFs Missing	% with MAF
1996	14	18	44%
1997	14	15	48%
1998	23	15	61%
1999	15	19	44%
2000	15	14	52%
2001	37	23	62%
2002	29	20	59%
2003	22	26	46%
2004	12	9	57%
2005	2	1	67%
Total	**183**	**160**	**53%**

[30] Green background indicates MAF was almost always present, red indicates MAF was almost never present, and blue indicates MAF was occasionally present.

Table 5-4. Comparison of Vehicle Make Distributions between Kansas City Study Data and Maryland Registration Data

Make	Vehicles in Maryland Registration Data	Vehicles in Kansas City Study Data	Vehicles in Maryland Registration Data (%)	Vehicles in Kansas City Study Data (%)
ACURA	36995	2	2.2%	0.6%
BUICK	37535	10	2.3%	2.9%
CHEVROLET	213545	31	13.0%	9.0%
CHRYSLER	42683	13	2.6%	3.8%
DODGE	108052	31	6.6%	9.0%
FORD	250404	51	15.2%	14.9%
GEO	0 [Geo=Chevrolet]	1	0.0%	0.3%
GMC	37923	4	2.3%	1.2%
HONDA	191579	57	11.6%	16.6%
HYUNDAI	33637	2	2.0%	0.6%
INFINITI	13411	1	0.8%	0.3%
ISUZU	7979	5	0.5%	1.5%
JEEP	59256	10	3.6%	2.9%
KIA	13250	8	0.8%	2.3%
MAZDA	34472	7	2.1%	2.0%
MERCURY	33026	6	2.0%	1.7%
MISTUBISHI	25476	3	1.5%	0.9%
NISSAN	90401	14	5.5%	4.1%
OLDSMOBILE	16714	4	1.0%	1.2%
PLYMOUTH	9609	7	0.6%	2.0%
PONTIAC	35134	5	2.1%	1.5%
SATURN	28283	12	1.7%	3.5%
SUBARU	24548	3	1.5%	0.9%
TOYOTA	237937	52	14.5%	15.2%
VOLKSWAGEN	40046	1	2.4%	0.3%
VOLVO	23645	3	1.4%	0.9%

5.2.3 Operation Types

ERG's recommended approach for estimating instantaneous fuel economy is provided in the following subsections.

Operation on Oxygenated Fuels – In the U.S., fuels are oxygenated (they have an ethanol content typically up to 10% or more). Due to the higher oxygen content of an oxygenated fuel, the amount of air required per unit of fuel for stoichiometric combustion is reduced in comparison with non-oxygenated fuels. Modern closed-loop controlled vehicles automatically adjust the air/fuel ratio, so the ethanol content of the fuel must be known to accurately calculate the fuel economy as described above. For pure ethanol, the air/fuel ratio is approximately 9.0.[31] Various blends will have stoichiometric air/fuel ratios between 9.0 and 14.7, and are roughly: [32]

- E0 (gasoline: 0% ethanol): 14.65
- E5 (5% ethanol): 14.36
- E10 (10% ethanol): 14.08
- E15 (15% ethanol): 13.79
- …
- E85 (85% ethanol): 9.85
- E100 (100% ethanol): 9.0

E10 therefore has a 3.5% difference in air/fuel ratio requirement than gasoline. This corresponds with the fact that E10 has an equivalently lower energy content than conventional gasoline (pure ethanol has a lower heating value of approximately 76,000 BTU/gal, while gasoline has a lower heating value of approximately 115,500 BTU/gal[33]). As described in Section 5.1, ERG's recommended approach for determining ethanol content is to collect regional fuel ethanol content data in each area in which the main study is being conducted (or assume regional or national averages based on the season, if this assumption can be shown to be acceptable).

Gasoline low- and mid-load operation (targeting stoichiometric) – Fuel economy under low- and mid-load operation of gasoline vehicles will be estimated as previously described for gasoline vehicles. It may be possible to obtain acceptably accurate fuel economy estimates using SAE J1979 mass air flow and lambda for vehicles that broadcast this information, but OEM-specific fuel injector rate information may be necessary to obtain accurate instantaneous fuel economy estimates for vehicles that do not broadcast mass air flow and lambda.

Cold-start (open loop) – A focus of this pilot study was to determine method(s) for estimating accurate instantaneous fuel economy when a vehicle is in cold-start operation (immediately after a "cold" vehicle is turned on). During this time, if the ambient temperature is sufficiently low, the engine operates in "open loop," which means feedback from the oxygen sensor is not available for tailoring the fuel to match the amount of air entering the engine. Also during this period of "blind" operation (no oxygen sensor feedback), the engine is generally programmed to provide a fixed air/fuel ratio that is richer than stoichiometric to improve cold

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[31] Kyung-ho, Ahn; Stefanopoulou, Anna; Jiang, Li; Yilmaz, Hakan; Ethanol Content Estimation in Flex Fuel Direct Injection Engines Using In-Cylinder Pressure Measurements, SAE article 2010-01-0166, 2010.
[32] "Technical Assessment of the Feasibility of Introducing E15 Blended Fuel in U.S. Vehicle Fleet, 1994 to 2000 Model Years", Ricardo, Inc., Prepared for: Renewable Fuels Association, Sept 10, 2010.
[33] http://www.eia.gov/oiaf/analysispaper/biomass.html

drivability while the engine warms up.[34] Since vehicles do not target stoichiometric operation and no real-time information is available regarding the actual air/fuel ratio being provided during this operation, again the use of OEM-specific queries of fuel injector rate may a way to achieve instantaneous fuel economy estimates for cold-start operation. If fuel rate is not available as an OEM-specific query, it may be possible to use fuel injector pulse width (this would also be an OEM-specific query) to estimate instantaneous fuel consumption. The relationship between fuel injector pulse width and fuel rate (as calculated using another method such as mass air flow collected during closed-loop, or warmed-up operation) would be needed to correlate fuel injector pulse width with fuel rate. This would also require some assumptions regarding fuel density and pressure during these various periods of operation. As another alternative, "target" air fuel ratios, such as those given by commanded equivalence ratio broadcast during cold-start operation, may also be used to estimate fuel rate during "blind" operation. Additional information on using commanded equivalence ratio is provided in Section 5.5.3.

Wide-open throttle (enrichment) and deceleration (fuel cut-off) – Strategies for estimating instantaneous fuel economy during enrichment mode and fuel cutoff mode (open loop operation) may be similar to those for gasoline low- and mid-load operation. It may be possible to obtain acceptably accurate fuel economy estimates using SAE J1979 mass air flow and lambda (if lambda is broadcast during these non-stoichiometric operating modes), but emissions modeling with standard PIDs (as shown in Section 5.5.3) or OEM-specific fuel injector rate information is probably necessary to obtain accurate instantaneous fuel economy estimates for vehicles that do not broadcast mass air flow and lambda (or if lambda information is not broadcast during open-loop operation). Additional information on strategies to estimate fuel economy for various vehicle and technology types is provided in the following section.

5.2.4 Summary of Measurement Strategies based on Vehicle and Fuel Types

Table 5-5 provides a summary of data collection strategies that could be used in a full-scale study. Rankings are provided for which strategy is believed to be the "best" approach for collecting data for each of the vehicle technology combinations. "Best" strategy rankings include consideration of cost and accuracy; rankings could vary depending on the suitability of the accuracy relative to the costs. A rank of "1" indicates we feel this is the best approach, a "2" indicates this is the second choice, and so on. These rankings could be revised as more information becomes available. For example, if PID 5E (standard fuel rate) is not found to have suitable accuracy, then another approach would be recommended.

[34] http://autorepair.about.com/library/glossary/bldef-590.htm

As can be seen in Table 5-5, at this point in time, collection of PID 5E is the recommended approach for determining fuel consumption, if this PID is available for a particular vehicle and found to be acceptably accurate (SAE J1979 specifies a scaling factor of 0.05 liters/hour per bit on PID 5E). If manufacturer-specific (enhanced) PIDs are required, ERG recommends that the fuel rate be acquired, if available (rather than fuel mass/volume per injection or injection duration). However, if fuel rate is not available, then fuel mass/volume per injection or injection duration may be acquired and correlated to fuel rate during stoichiometric operation calculated with the vehicle's mass air flow (as shown in the table), or using injector calibration data. When using standard PIDs, fuel economy during non-stoichiometric operation may be estimated using O_2 sensor data and/or calculated load (both standard PIDs). Other strategies are also recommended based on what we currently know about acquisition of the various parameters and accuracy of fuel consumption estimates using the various PIDs. These recommendations could change based on future research, such as that described in Section 5.6 (Future Proposed Analysis).

Table 5-5. Logging Strategies for Various Vehicle, Fuel, and Data Types[35]

Vehicle / Fuel / Data Type	Standard PIDs				Enhanced PIDs				
	Fuel rate (Std PID 5E)	MAF	MAP	O_2 Sensor and/or Calculated Load	Mfr-specific fuel rate (mass or volume)	Injector mass or flow rate per injection(s)	Mfr-specific injector time duration	Mfr-specific battery state of charge	Mfr-specific A/C compressor status
Fuel Consumption									
Gasoline MAF with wide-band O_2 sensor	1	2		2					
Gasoline MAF with narrow-band O_2 sensor	1	2, 4, 5		2	3	4	5		
Gasoline MAP with wide-band O_2 sensor	1		5	5	2	3	4		
Gasoline MAP with narrow-band O_2 sensor	1		5	5	2	3	4		
Diesel	1	3, 4, 5	6	3, 4	2	3	4		
Other Data									
Hybrid battery state of charge								1	
A/C compressor on/off									1

[35] Strategy rankings (1-5) could vary depending on cost and desired accuracy. These could also change based on results of future proposed analysis described in Section 5.6.

5.3 Datalogger Market Research and Selection

Based on the requirements described above and listed in Table 5-1, ERG developed a list of criteria to be used to evaluate dataloggers for this study, and these are provided in Table 5-6. Unlike the general acquisition specifications listed in Table 5-1, Table 5-6 criteria were tailored according to our specific research objectives. For example, since “battery state of charge” and “air conditioning compressor status” are both parameters that would need to be acquired using enhanced PIDs, “battery state of charge” and “A/C compressor status” were replaced with the “Other enhanced PIDs” category shown in Table 5-6. The criteria shown in Table 5-6 were used to identify which dataloggers appeared to be the most suitable candidates for further evaluation during this pilot. Clarifying information regarding some of the parameters listed in Table 5-6 is given in the subsections that follow the table.

5.3.1 Communication Protocol Capabilities

OBD systems send data using various types of communication protocols. Several protocols were in use between 1996 and 2004, but between 2004 and 2008, all U.S.-based vehicles were phased into a common protocol, Controller Area Network, or CAN. Since any light-duty 1996 or newer vehicle could be selected for the main study, the datalogger to be selected must be able to communicate on CAN as well as the earlier “legacy” protocols.

5.3.2 Enhanced PID Capabilities

While quite a bit of information may be obtained from SAE J1979 standard PIDs, it was clear from the study requirements that additional information beyond that available from the standard PID datastream would likely be required. This includes information such as air conditioning compressor on/off status and hybrid battery state of charge as well as powertrain PIDs relating to fuel consumption for diesels, vehicles that do not broadcast mass air flow, and non-stoichiometric operation (when lambda is not available). The two primary costs associated with collection of enhanced PIDs are for purchase of the enhanced PID database from each vehicle manufacturer (or a central repository such as the Equipment and Tool Institute) and incorporation of the enhanced PID data into the datalogger’s software in order to allow the datalogger to request, capture, decode, and present the desired enhanced PID data for all vehicles in the fleet.

Table 5-6. Datalogger Evaluation Requirements for In-Use Fuel Economy Study

Acquisition Capabilities
Date / Time Stamp
Sleep and power-up on signal (i.e., no user input required)
Adjustable acquisition rate (1 Hz to 2 Hz, variable by parameter)
# of simultaneous parameters that can be acquired at 1 Hz, 2 Hz
Can logger collect vehicle info? (i.e., Mode $09 VIN request)
Can logger automatically establish connection with vehicle when key is turned on?
Can logged data base exported to a *.csv or other type of delimited file?
Communication Capabilities
SAE J1850, PWM (Ford), VPW (GM)
ISO 14230 (KWP 2000)
ISO 9141-2 (KWP2000, Chrysler, Euro, Asia)
ISO 15765 (11898) (CAN)
Enhanced powertrain PIDs? (i.e., fuel rate for diesels and vehicles without MAF)
Other enhanced PIDs? (i.e., hybrid battery, A/C status, climate control, cabin temp)
Other Measurements
GPS (and accuracy)
Internal (cabin) temp
Road Grade
Accelerometer (2 Hz capability desired)
Other Datalogger Specs
Internal Memory (> 2 GB internal or removable SD card?)
Can logger be configured for which standard PIDs to acquire, by vehicle?
Method of configuration: (i.e., must each logger be individually set up, or can a configuration file be imported into the logger's memory?)
Does logger install directly onto the OBDII DLC or connect by cable?
Size / weight
Temp range
Standby current draw (to ensure it will not drain batteries)
Does logger have Wi-Fi, cellular, Bluetooth?
Does logger have operating indicators (i.e., LED) that could indicate malfunction?
What is the accessibility of the manufacturer and / or supplier?
Other
Other comments
Order turnaround time
Base cost
Additional costs
Total Cost
Overall Assessment A = A very attractive candidate B = Perhaps suitable but not ideal C = Probably not suitable

5.3.3 Data Storage and Transmission

Cellular transmission – Cellular transmission offers attractive benefits, but also results in some technical challenges and higher costs. Cellular coverage and signal quality will vary, and the system behavior must be designed for reliable data collection and transmission under these conditions. At a minimum, the data must be capable of being stored for a sufficiently long period of time, perhaps weeks, before it is reliably transferred to the central server. For cost and technical reasons, it may not be practical to stream the vehicle data continuously over an open data channel to an Internet server, so the system must packetize the data in nonvolatile memory and use any opportunity to transfer the stored data to the server, including after the vehicle is turned off. Off-hour transmission and use of binary language can reduce costs due to lower transmission rates and data volumes. While 2 Hz acquisition is desired for certain parameters (such as vehicle speed and acceleration), minimizing acquisition rates for other less-transient or less-critical parameters (such as engine coolant temperature) can reduce the amount of data that needs to be stored and transmitted.

Cellular machine-to-machine (M2M) data collection has become very common in recent years. Both AT&T and T-Mobile allow their networks to be used for this purpose, with T-Mobile perhaps being the most aggressive in promoting this practice. Any carrier data plan can be used for M2M, including prepaid plans from AT&T and monthly plans from T-Mobile. These plans currently cost about $30 per month and provide much more data (5GB is typical) than would likely be required for a single month of data for a single vehicle. Third party service providers such as Raco Wireless provide cellular data plans which, while more expensive per byte (currently about $4.85/month for 25MB), cost less in many M2M applications that do not require large amounts of data per month.

The use of M2M cellular communications also requires an Internet server programmed to accept, store, and present the data received from the fleet of cellular M2M data sources. Many companies that sell dataloggers offer this service, and there are other small companies that can also provide this service. The Internet server must be customized for the type and format of the data collected by the remote data sources.

Wi-Fi transmission – The use of Wi-Fi as an option for data transmission was also considered for this study. For this option, the datalogger would be equipped with a Wi-Fi transmitter that could be used to transfer the data (again, in packets) to a local project server developed for this study. However, because of network security issues, hot spots (Wi-Fi receivers connected to the Internet) would need to be used in centralized study locations of interest in order to periodically collect data from the each vehicle. Alternatively, participant's home routers could be used as receivers. However, because of the broad geographic distribution of anticipated study vehicles and issues associated with establishing numerous Wi-Fi networks or connections, this option was not considered to be a feasible solution at this time.

Onboard storage – Many dataloggers (including those using a SD card or a micro-SD card) can commonly store 32 GB or more of data. ERG's preliminary assessment of memory requirements (1 to 1.5 GB of data for each vehicle over one year, depending on parameters selected and acquisition rates of each of the parameters) is well under the 32 GB limit of micro-SD cards. However, one fundamental issue with onboard storage is the inability to remotely verify that valid data is being collected without somehow retrieving and downloading the data. Even if a datalogger has an indicator to show the vehicle operator if the logger is functioning, data acquisition problems can still occur undetected. Therefore, although onboard storage is feasible, it is highly preferable to use on-board storage with some form of data transmission.

Using the criteria listed in Table 5-6, ERG performed market research to identify all dataloggers, software, hardware or components that could be used as a datalogging solution (or partial solution) for this study. ERG also investigated independently developing a datalogging system that would meet project needs. As described in Table 5-1, ERG's general approach was to acquire as much data as possible from SAE J1979 standard PIDs from the vehicle's ECU OBDII-port or devices integral to the datalogger (GPS, thermocouples, accelerometers). Enhanced PIDs or external sensors would also be required in order to acquire some of the data listed in Table 5-1.

ERG performed market research to identify companies that offer products that may be suitable for use in the main study. Companies and products were identified using Internet research, information obtained from research during prior projects, information previously collected at conferences and others' referrals of companies. Products from the following companies listed in Table 5-7 were evaluated and screened for suitability in this study.

Table 5-7. Companies Whose Products were Evaluated

ACR	Drew Technologies	Oxford Technical Solutions
Agnik	Ease	Persentech
ANTX	eDAQ-lite	PLX
Auterra	Equipment & Tool Institute	RaceLogic
AutoEnginuity	Fleetwatch	ScanTool.net
B&B Electronics	Georgia Institute of Technology	Sensors
Cloudcar	HEMData	Si-Gate
Compact Instruments	Hydro Electronic Devices	Solidica
CONTROLTEC	Injectoclean	Squarrel
Corsa Instruments	Isaac Instruments	Telargo
CSM	iTds	Trimble
Datron Technology	Linear Logic	Universal Tracking Technologies
Davis Instruments	Networkfleet	Vector
Dearborn Group	Ono Sokki	

Information was gathered on products offered by each of these companies to determine if any of them appeared to warrant additional evaluation. Those that did appear to warrant additional evaluation were added to a "short list" for evaluation using some or all of the criteria listed in Table 5-6. The following dataloggers were given this additional evaluation:

- Auterra Dashdyno SPD
- AutoEnginuity #ST06 plus expansion options
- Cloudcar (MIT)
- ControlTEC CT1000
- Dearborn Group Gryphon
- Drew Technologies CarDAQ
- Drew Technologies / HEMData AVIT
- HEMData DAWN Mini
- LiveDrive i2d (iTds)
- Persentech CVS43
- Persentech CD

Highlights of each of the dataloggers that were evaluated using some or all of the criteria listed in Table 5-6 are listed in Table 5-8.

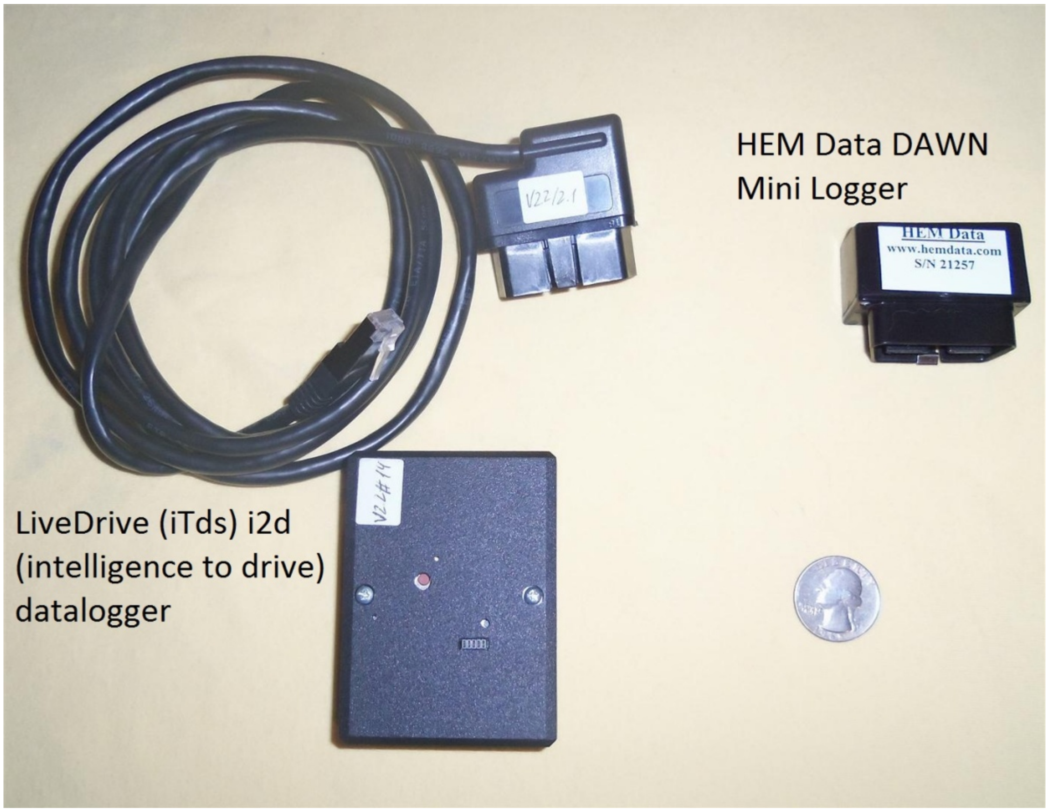
Table 5-8. Assessment of the Most Suitable Datalogger Candidates

Datalogger Name	Suitability for Use in Study	Limitations of Use in Study	Approximate Cost	Score[36]
Auterra Dashdyno SPD	Appears to be a fairly well developed product, CAN and legacy protocols, GPS capable, analog and digital inputs, removable memory, affordable.	Appears to have limited control of acquisition rate, the enhanced PIDs necessary for this study do not appear to be available, touch screen interface not ideal for this type of study.	$300 base, plus $50/each mfr for enhanced PIDs	B-
AutoEnginuity #ST06 plus expansion options	Collection of CAN and legacy protocols plus MANY enhanced PIDs. Fairly affordable.	This appears to be a PC-based software solution rather than a stand-alone datalogger. Requires PC to operate.	#ST06 is $250, plus $230 each for Chrysler and Honda modules	B-
Cloudcar (MIT)	Reported to meet most of the project needs, open source flexibility. Requested but did not receive data samples, specification sheets, or additional info.	Current form of logger does not appear to have legacy protocol support. ERG might be able to make these modifications.	Not obtained	C+
ControlTEC CT1000	Appears to be a versatile unit with GPS, cellular, removable memory. Company has strong automotive background.	Relatively costly and currently no legacy protocol support. Possibly more for OEMs and lab development.	$2500 - $3000 base, data and communication plan, $150 - $200 / month. Future plans (2013?) for CT500 @ $1000 base	C
Dearborn Group Gryphon	Appears to be a versatile logger, auto on/off and configurable that can capture CAN and legacy protocols, with CF memory capability.	Relatively costly, possibly more for OEMS and lab development. Does not appear to have GPS.	Logger and software was $3400 during prior survey.	C
Drew Technologies CarDAQ	Appears fairly versatile, CAN and legacy protocols, GPS, large internal memory.	Relatively costly, does not appear to have sleep mode or enhanced PID capability, system appears to require interface programming.	$1900	C

[36] A = a very attractive candidate, B = perhaps suitable but not ideal, C = probably not suitable

Datalogger Name	Suitability for Use in Study	Limitations of Use in Study	Approximate Cost	Score[36]
Drew Technologies / HEMData AVIT	Appears fairly versatile and rugged, CAN and legacy protocols, GPS, Wi-Fi, large internal memory	Relatively costly, unit is 10" x 5" x 1" box and appears to require additional system development to meet study needs.	From prior survey, $2300 excluding software and GPS	C
HEMData DAWN Mini	Appears to offer most of what we need, small, plugs directly onto DLC. Provides fuel economy for MAF vehicles. Unit appears suitable for this type of study.	Single units are relatively costly, but price drops for quantity purchases. No barometric altimeter. Currently no cellular (about 4 months). Currently no legacy (expected, but may be expedited for a fee).	$1000 - $2300 based on volume discounts, see Table 6-3	A-
LiveDrive i2d (iTds)	Appears to offer most of what we need, includes cellular and data service, very affordable. Barometric altimeter for road grade, reportedly provides instantaneous fuel economy for all technology types.	Appears to be still undergoing development, does not mount directly onto DLC, appears to have limited control of acquisition rate, limited ability to acquire / modify standard PIDs, unable to review fuel economy estimates.	$200, see Table 6-4	B
Persentech CVS43	Appears to be an autonomous device, SD card acquisition, CAN and legacy protocols, GPS, internal cellular, moderate price.	Appears to have a touchscreen for user input, no enhanced PIDs.	$800	C
Persentech CD	Appears to be an autonomous device, SD card acquisition, CAN and legacy PIDs, GPS, internal cellular, moderate price	Does not appear to have cellular, accelerometer, barometric altimeter or enhanced PID capability.	$500	B

Based on the short-list review of each of the eleven candidates, ERG selected two loggers for hands-on evaluation and testing: the HEMData DAWN Mini and the LiveDrive (iTds) i2d, which are shown below.



A summary comparison of the features and functionality of the HEMData DAWN Mini and the LiveDrive (iTds) i2d loggers is provided in Table 5-9. Limitations of each of the loggers (with respect to requirements for this study) are shown in yellow shading. As noted in the table, not all of these features were verified by our testing. Observations arising out of our testing and review are summarized in the following section.

Table 5-9. Comparison of i2d and DAWN Mini Reported Features

Feature	LiveDrive i2d	HEMData DAWN Mini
auto sleep / power-up	Yes	Yes
adjustable data acquisition rate	Limited	Yes
Internal clock	No	Yes
auto-establish connection	Yes	Yes
Size and ease of installation	Fair	Good
GPS	Yes	Yes
accelerometer	Yes	Future[37]
Internal thermocouple	Not verified[38]	Future[31]
on-board data storage	Yes, 2 GB internal	Yes, up to 32 GB card
CAN protocols	Yes	Yes
legacy protocols	Not verified[32]	Future[31]
Standard PID selection configurable	Planned[39]	Yes
enhanced PIDs (powertrain / other)	No	May be added[40]
Cellular data transmission	Yes	May be added[33]
supplier accessibility	Fair	Good
FE calculations from standard PIDs	Not verified [32]	MAF vehicles only
FE estimates for all vehicle types	Not verified [32]	MAF gasoline only
barometric altimeter	Yes	No
Bluetooth	Yes	No

5.4 Evaluation of HEMData Dawn and LiveDrive I2d Dataloggers

ERG ordered both a HEMData DAWN Mini and a LiveDrive (iTds) i2d datalogger for evaluation in this study. Both units were received and were tested to evaluate their suitability for use in the study. A summary of each evaluation is provided below.

5.4.1 LiveDrive i2d

ERG was not able to thoroughly evaluate the LiveDrive i2d unit, as it was still undergoing development, and many of the features expected to be available were not currently functional on our unit during the period of evaluation. This unit reportedly calculates fuel economy for all vehicle types, including gasoline vehicles that report mass air flow, gasoline vehicles that do not report mass air flow, and diesel vehicles. It is not known how accurate the fuel economy estimates are or how precisely the i2d unit adjusts fuel economy estimates for non-stoichiometric operation. Instantaneous fuel economy estimates were not provided by the unit

[37] HEMData is currently making this modification with an estimated completion of September 2013.
[38] ITDS reports the i2d does have this functionality, but this was not verified during ERG's testing.
[39] The i2d logger currently acquires a fixed set of standard (SAE J1979) PIDS, but ITDS reports longer-term development plans include adding the ability to allow the user to acquire additional standard (SAE J1979) PIDs of their choice (i.e., add lambda or fuel trim to the list of PIDs to acquire)
[40] See costs in Section 6.1.

ERG evaluated for this study, although overall average fuel consumption and CO_2 estimates were provided on i2d's website for the vehicles ERG tested.

The i2d unit comes in two configurations, one with the GPS and cellular antennas mounted inside the datalogger housing (shown in the figure) and one in which the GPS and cellular antennas are a separate component connected to the datalogger housing with two small coaxial cables. This separate antenna configuration allows the antenna to be mounted in a separate location from the datalogger housing, which could result in better reception, but this also results in additional wiring that can become caught in the driver's or passenger's feet (or pedals) if not routed carefully. The datalogger housing with the internal antennas can also be mounted in a windshield, and this appeared to provide adequate GPS and cellular signal service. Although remote mounting by cable connection is not ideal, motorist installation may still be possible, as this is similar to mounting a radar or laser detector or mounting an aftermarket GPS system (remote box attached to a cable). The i2d unit appears to be a high-quality, well-manufactured unit. No memory card is available (without opening the unit). As shown in the figure, the datalogger housing is relatively small, and attaches to the DLC with a cable. Some routing of the cable is required for installation. The red button on the datalogger may be used to align the X, Y, and Z coordinates of the 3-dimensional accelerometer after the logger has been installed.

After our installation of the i2d logger, the unit did automatically power up, and it did switch into sleep mode when the test vehicles were shut down. The i2d also automatically established an OBD connection and collected OBD data, along with GPS, barometric pressure, and accelerometer data on the vehicles on which it was installed. The information that was collected was wirelessly broadcast (via cellular communication) to an Internet-based server, where the data could be viewed and downloaded. However, as this Internet server was an interim site used for product development, we were not able to verify the instantaneous fuel rates that will reportedly be provided on the production server. These loggers were only tested on vehicles with CAN communication protocol (so its ability to communicate with vehicles with the older legacy protocols was not evaluated).

As Table 5-9 indicates, the ability of the user to adjust the acquisition rate of the i2d unit is limited. Although the acquisition rate can be adjusted, it is defined by the i2d server and is common to all units in order to ensure compatibility with the software running on the i2d server. The i2d logger has an internal timer (rather than a clock), and timestamps shown for each record of data correspond to the server time (when the information was received by the server) and the GPS time (at the moment the data was logged). Since GPS is not acquired at precisely 1 Hz, there is a possibility of two records of data having the same time stamp, or two consecutive lines of data having time stamps more than one second apart. I2d estimates a deviation of approximately 30 seconds over a 24-hour period. A revised version of the i2d logger with an internal clock is planned, and in the future it may be possible to adjust the acquisition rate, by PID, to optimize data acquisition.

The i2d unit collected and reported several standard SAE J1979 PIDs, including engine RPM and vehicle speed, engine load and throttle position, mass air flow, intake manifold absolute pressure, intake air and coolant temperatures and barometric pressure. ERG was not able to modify this list of PIDs or select additional PIDs (such as oxygen sensor voltage, lambda or fuel trim) to acquire. I2d reported future development plans including modification of the webserver and i2d firmware to allow the user to select additional PIDs for collection, although the timeline for these modifications was not provided. I2d also indicated that the collection of additional PIDs could slow the OBD acquisition rate to slower than 1 Hz. It may be possible to reduce the acquisition rate of some PIDs (such as engine coolant temp) to increase capacity of other PIDs at a higher rate.

Because of these limitations, we were not able to further evaluate the i2d logger during this pilot, but we do feel that this system is a promising candidate for this type of study once development has progressed. Additional review of this system is warranted for use in any follow-up study.

5.4.2 HEM Data DAWN Mini

ERG has prior experience with HEM Data data acquisition systems and also the DAWN Mini logger from prior projects. In addition, we are aware of a number of other organizations that use HEM Data products, including the U.S. Environmental Protection Agency, the U.S. Department of Energy, the U.S. Army, the California Air Resources Board, Toyota, ExxonMobil and others. HEM Data has specific experience collecting and analyzing the type of data necessary for this study, such as instantaneous fuel economy using both standard SAE J1979 PIDs (with correction for deviation from stoichiometric for vehicles that report lambda) and also fuel rate using enhanced OEM-specific PIDs. HEM Data also has experience in collecting hybrid vehicle battery state of charge (using enhanced PID data acquisition as well as external input sensors).

As shown in the figure, the DAWN Mini unit is small and plugs directly onto the vehicle’s OBDII DLC. A micro-SD card is inserted into the front of the logger (the end opposite the DLC pins which cannot be seen in the figure). The advantage of a logger that mounts directly onto the vehicle's DLC is that no connecting cable to datalogger routing is required. This is particularly advantageous in vehicle test programs in which the participants are responsible for mounting their own dataloggers, as this eliminates the problem of hanging wires getting caught up in the driver's feet, brake, accelerator, or clutch pedals. However, DAWN's micro-SD card does extend beyond the logger, and it is possible to dislodge the card during datalogger installation (or possibly by a foot inadvertently hitting the logger). This could result in an inability of the logger to record the vehicle's OBDII data and a loss of study data. HEM Data did indicate that it is possible to obtain a unit with only internal memory (no external micro-SD card). Although no price quotes were provided, HEM Data indicated that a revised design with internal memory would result in a reduced cost.

The unit ERG acquired for this evaluation performed as indicated in Table 5-9. The logger is equipped with an accelerometer and an internal thermocouple, although the current version of firmware does not support these two features (the unit is being upgraded to receive this functionality by the fall of 2013). Also, as shown in this table, the current version of the DAWN Mini does not have the capability of collecting data on any of the legacy protocols (although the unit is being upgraded to receive this functionality by the fall of 2013 as well).

The DAWN Mini provided instantaneous fuel economy estimates for vehicles that broadcast mass air flow. These instantaneous fuel economy estimates were based on gasoline (no oxygenate) and were adjusted for non-stoichiometric operation for vehicles that broadcasted lambda (output from a wide-band oxygen sensor). For vehicles with narrow-band oxygen sensors, the fuel economy estimates were based on the assumption of stoichiometric operation (no lambda correction was applied). The DAWN Mini does allow the user to fully configure which standard (SAE J1979) PIDs to acquire, but the base DAWN Mini does not include the capability of collecting enhanced PIDs (i.e., for battery state of charge and fuel rate on non-MAF vehicles). Costs for enhancing the base unit with enhanced PID collection capability for some vehicles are provided in the cost section of this report. Due to lack of availability of data from some vehicle manufacturers, enhanced PID data collection is not currently possible for all on-road vehicles, and is limited to those vehicles shown in the cost tables. HEM Data has experience in collecting this data from Ford and Toyota, and provided a sample of enhanced Toyota data (fuel rate) to ERG to evaluate against fuel rates calculated using standard SAE J1979 PIDs. This analysis is provided in Section 5.5.2.

Since each PID must be requested by the datalogger each time data is required, delays in receiving the response and also in sending consecutive requests could cause a slow acquisition rate. During testing, ERG did not verify the HEM Data DAWN's messaging rates, but HEM

Data reports the DAWN's PID requests are broadcast at a frequency determined by the selected acquisition rate. For example, if 20 PIDs are selected at an acquisition rate of 1 Hz, each PID request is broadcast at 0.05 second intervals, so for the 20 PIDs acquired at this rate, the total delay would be approximately 950 ms (plus the response delay for the final PID), and the cycle would resume again (PID 1 request) at 1000 ms (1 second) after the prior sequence of requests. In this scenario, we would expect to maintain a 1 Hz acquisition rate. Similarly, for a 2 Hz acquisition rate, each PID request would be broadcast at 0.025 second intervals, so the total delay would be approximately 0.475 ms (plus the response delay for the final PID), and the cycle would resume again (PID 1 request) at 0.5 seconds after the prior sequence of requests (a 2 Hz acquisition rate). HEM Data testing on a late model vehicle showed a response delay generally ranging between 2 and 9 ms. Different vehicles may have different response rates, and critical operation systems will have a priority on some vehicle networks, so the actual response rates could vary based on total traffic on the network. HEM Data reports most vehicles networks (including legacy protocol networks) should communicate at an acceptable rate. GM's SAE J1850 VPW is 10 kilobits per second and should accommodate 20 PIDs at 1 Hz, Ford's SAE J1850 PWM is 40 kilobits per second, but ISO 9141 (Chrysler, European and Asian vehicles) at 3 kilobits/second is relatively slow. Additional testing may be required in order to ensure that a suitable acquisition rate is possible with these vehicles, and for these vehicles, the number of PIDs to be acquired should be minimized in order to maintain a 1 Hz acquisition rate.

The HEM Data DAWN's GPS acquisition rate is currently set at 5 Hz, although it can be set anywhere from 1 to 10 Hz in the firmware (this is a manufacturer adjustment). The DAWN datalogger draws 80 mA when active, and standby current drain is approximately 1 mA.

During testing, the HEM Data DAWN was unobtrusive and stayed attached to the DLC on all the tests that were performed (although the metal retention clip that helps keep the logger attached to the DLC was pulled off and lost during dynamometer testing, which could be a problem in a full-scale field study). As previously noted, there is a potential for the micro SD card to become dislodged during installation or use (if the card is knocked), as the card is retained only by friction and does not lock in place. However, HEM Data stated a system design modification could be made, if desired, to provide a logger with only internal memory (at a reduced cost from the current unit). Also, the DAWN Mini's DLC pins appear to consist of unplated copper, which could lead to galvanic corrosion over a long duration study, although HEM Data reports no such issues in other similar studies (over a year of data acquisition) they are currently conducting. During testing, it was noted that due to the datalogger's heat generation, the internal logger temperature reading that would be recorded by the logger would not represent the cabin temperature, and therefore might not provide a reliable signal for air conditioning on/off status.

Because of the accuracy issues associated with calculating fuel rates for non-MAF and diesel vehicles, the base HEM Data DAWN Mini only provides fuel rates for vehicles that broadcast mass air flow. It may be possible to collect enhanced PIDs to calculate fuel rate for some non-MAF and diesel vehicles, or alternatively it may also be possible develop fuel economy estimation methodologies for non-MAF and diesel vehicles using standard SAE J1979 parameters, as described in Sections 5.6.1 and 5.6.3.

The current version of the DAWN Mini does not offer cellular capability, but HEM Data reports this is being added and should be available within a few months. The cellular service plan could be established with the carrier of choice, and HEM Data offers an Internet-based server that could be used as a data repository for a one-time setup fee. The DAWN Mini can reportedly obtain different parameters at different rates (i.e., 2 Hz for vehicle speed and 0.1 Hz for engine coolant temperature), although this was not verified during our testing. During discussions regarding this study, HEM Data offered several suggestions to reduce cellular transmission costs (these are strategies HEM Data is applying in one of their current studies):

- Acquire PIDs at differing rates (some PIDs such as speed or acceleration may be needed at 2 Hz, while other PIDs such as ambient temperature may be acquired at 0.1 Hz, for example)
- Transmit data in binary language, rather than text language, to reduce data size
- Transmit data during off-hours, such as between 2 a.m. and 5 a.m.

Overall, with some modifications (such as addition of legacy protocol capability, accelerometer data, and cellular communications) the HEM Data DAWN appeared to be a suitable unit for use in a full-scale fuel economy study. It is quick and easy to configure, offers configuration flexibility, and is simple to install and use. With the logger installed on the vehicle's OBDII DLC underneath the dash, there is a potential for loss of a GPS signal, although review of the data did show a GPS signal was generally available. Integral LEDs do indicate when the unit is active and in standby mode, although the exposed micro-SD card does pose a risk of loss of data without the user's knowledge (as stated previously, HEM Data indicated a future version of the logger could be provided with only internal memory, if desired). Inclusion of cellular data collection capability could help mitigate that risk as incoming data could be regularly monitored. Although this unit is small enough to be unobtrusive for most applications, it is possible that some vehicles will have DLCs located in locations that expose the DAWN

Mini, or prevent a vehicle's DLC cover to be in place when the datalogger is installed. However, this will be the situation with any datalogger, including cabled units.

5.5 Datalogger Validation

After datalogger selections were made, the dataloggers were validated using several methods:

- In-use functionality testing was performed to verify the overall functionality of the systems. A summary of observations from this testing is provided in Section 5.4, Evaluation of HEM Data DAWN and LiveDrive i2d Dataloggers.

- Second-by-second fuel economy results from portable emissions measurement system (PEMS) data from the Kansas City Light-Duty Vehicle Study[41] were compared with fuel economy estimates from paired OBDII data (standard SAE J1979 MAF / fuel trim) from the same study, results are provided in Section 5.5.1.

- Second-by-second fuel economy estimates from standard SAE J1979 parameters (MAF/wide-band oxygen sensor lambda data) were compared with paired fuel economy estimates calculated using OEM-enhanced fuel injector fuel rate data from the same test, results are provided in Section 5.5.2.

- Second-by-second fuel economy results from dynamometer testing were compared with fuel economy estimates from paired OBDII data (standard SAE J1979 MAF / narrow-band oxygen sensor data) collected over the U.S. EPA standard city cycle, the U.S. EPA standard highway fuel economy cycle and the US06 aggressive drive cycle. This testing was performed on a 2009 Saturn GDI for this study, and the results are presented in Section 5.5.3.

These validation methods were applied to the following types of vehicles:

- Port-fuel injected gasoline vehicles (narrow-band and wide-band oxygen sensors), Section 5.5.1 and Section 5.5.2

- A gasoline direction injection vehicle (with a narrow-band oxygen sensor), Section 5.5.3

- A hybrid vehicle (non-plug-in with a wide-band oxygen sensor), Section 5.5.2

[41] S. Kishan, A.D. Burnette, S.W. Fincher, M.A. Sabisch, W. Crews, R. Snow, M. Zmud, R. Santos, S. Bricka, E. Fujita, D. Campbell, P. Arnott, "Kansas City PM Characterization Study, Final Report," prepared for U.S. Environmental Protection Agency, prepared by Eastern Research Group, BKI, NuStats, Desert Research Institute, October 27, 2006, http://www.epa.gov/oms/emission-factors-research/420r08009.pdf.

Validation was performed under various conditions, including low and mid-throttle closed-loop (engine hot) operation, cold-vehicle operation (in which the vehicle operates in "open loop" mode), and high throttle operation in which the vehicle has a tendency to enter enrichment mode. Additional details and results of this testing are provided in the following subsections.

5.5.1 Validation using Kansas City PEMS Data

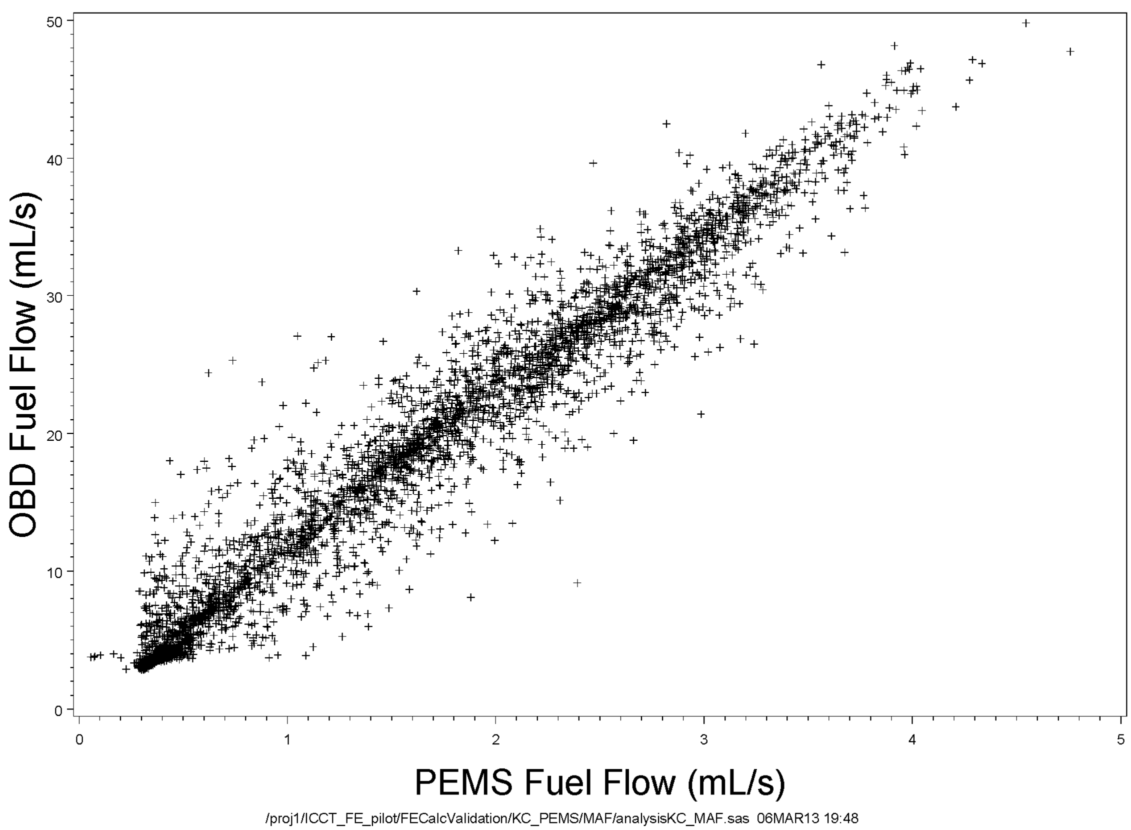
A subset of 19 test vehicles from the Kansas City Light-Duty Vehicle Study was used for this validation. The PEMS system used in this study recorded some of the standard SAE J1979 OBDII parameters along with the emissions and instrumentation data. Data was obtained from both on-road PEMS testing and also dynamometer testing over the LA-92 test cycle. Exhaust mass flow rate was collected using a flowmeter, so PEMS emission rates were available on both a concentration basis and also a mass basis for comparison with emission rates calculated using the OBDII data, which was recorded by the PEMS datalogging system. Mass air flow and manifold absolute pressure were both collected when available, along with other common OBDII parameters such as engine RPM, throttle position, engine coolant temperature, and intake air temperature. Although fuel trim was collected (bank 1 only), neither oxygen sensor nor lambda data are available, which limits our ability to adjust OBDII-based fuel economy estimates for non-stoichiometric operation. For this reason, the Kansas City data was primarily used to evaluate the feasibility of using fuel trim to tailor fuel economy estimates for non-stoichiometric operation and to determine the deviation of OBDII-based fuel economy estimates when assuming stoichiometric operation with those measured by PEMS, in particular during cold-start when vehicles may be operating in open-loop enrichment and also under high load, when vehicles may be operating in enrichment.

The 19 selected vehicles had valid data for the OBD mass air flow. The data for these vehicles was collected from December 2004 to April 2005. There were about 85,000 seconds of operation when the engine was on and the OBD and PEMs units were collecting data. We calculated the fuel flow using OBD parameters using the measured mass air flow, an assumed specific gravity for the fuel, and an assumed stoichiometric air/fuel ratio. Since these vehicles had narrow-band oxygen sensors but the output of the sensors was not in the dataset, these OBD calculations assume that lambda was 1. The PEMS unit reported fuel flow rate based on measured emissions concentrations and measured exhaust mass flow rate.

The fuel flow rate calculated from OBD information was compared with the fuel flow rate calculated from the PEMS measurements. For this comparison, we may regard the PEMS flow rate as the reference value.

Figures 5-2 and 5-3 compare the OBD- and PEMS-calculated fuel flows for two of the 19 vehicles in the dataset. The data times series were time aligned during the original QC-checking of the data immediately after data acquisition in 2005. These plots show that there is good agreement between the fuel flows for most of the points in the data. It should be noted that the line of agreement on these plots is not a one to one line. The ratio of the OBD calculated fuel flow to the PEMS calculated fuel flow is about 8 or 12. The fuel flow values calculated from the OBD data are clearly wrong since fuel flow at idle is typically about 0.5 mL/s. We believe this is due to a problem in the reporting of the units, which can be investigated and solved to show a one to one agreement.

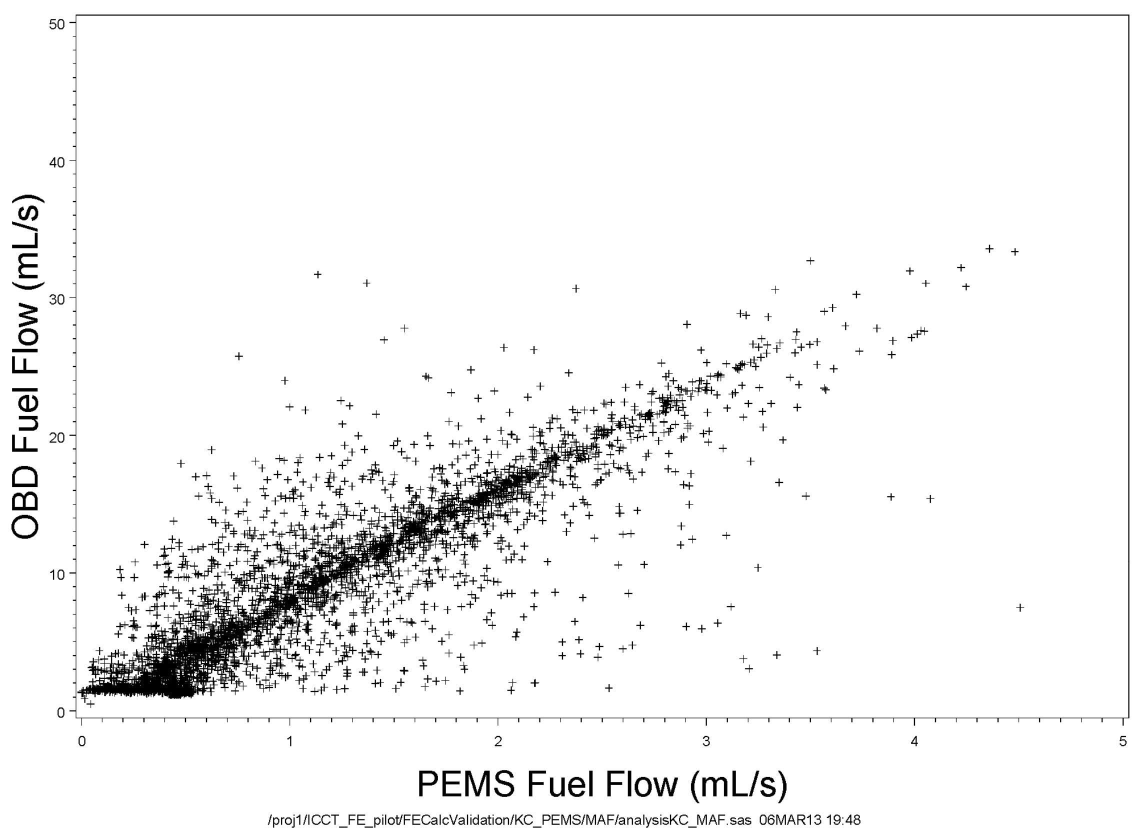
Figure 5-2. Comparison of OBD-Calculated Fuel Flow with PEMS-Measured Fuel Flow for Vehicle 1 (2003 Ford Explorer 4.0L)



An examination of the engine operating data indicated that most of the data on the plots is not from driving in enrichment. Even though the fuel flow calculations agree for much of operation of the vehicles, there is a scatter of points that do not lie on the line of agreement. Questions arise about whether the off-the-trend points are associated with enrichment or something else.

To further investigate, we examined events where the vehicle might be operating in enrichment. We first identified the times of engine start. This was done by looking for places where the oxygen went from 21% to around 0% while the carbon dioxide went from 0% to around 15%. After highlighting the vehicle starts, we further subsetted the data by keeping only the contiguous open loop operation that sometimes occurred immediately after an engine start. Open loop operation was identified by the OBD fuel trim parameter set exactly to zero immediately after engine start. Once the fuel trim diverged from 0, the vehicle was in closed loop operation.

Figure 5-3. Comparison of OBD-Calculated Fuel Flow with PEMS-Measured Fuel Flow for Vehicle 2 (2004 Toyota Corolla 1.8L)



Once the open loop starts were identified, we looked at the coolant temperature at the start to separate the open loop operation into "cold starts" (coolant temperature < 66F), and "hot starts" (coolant temperature > 66F).

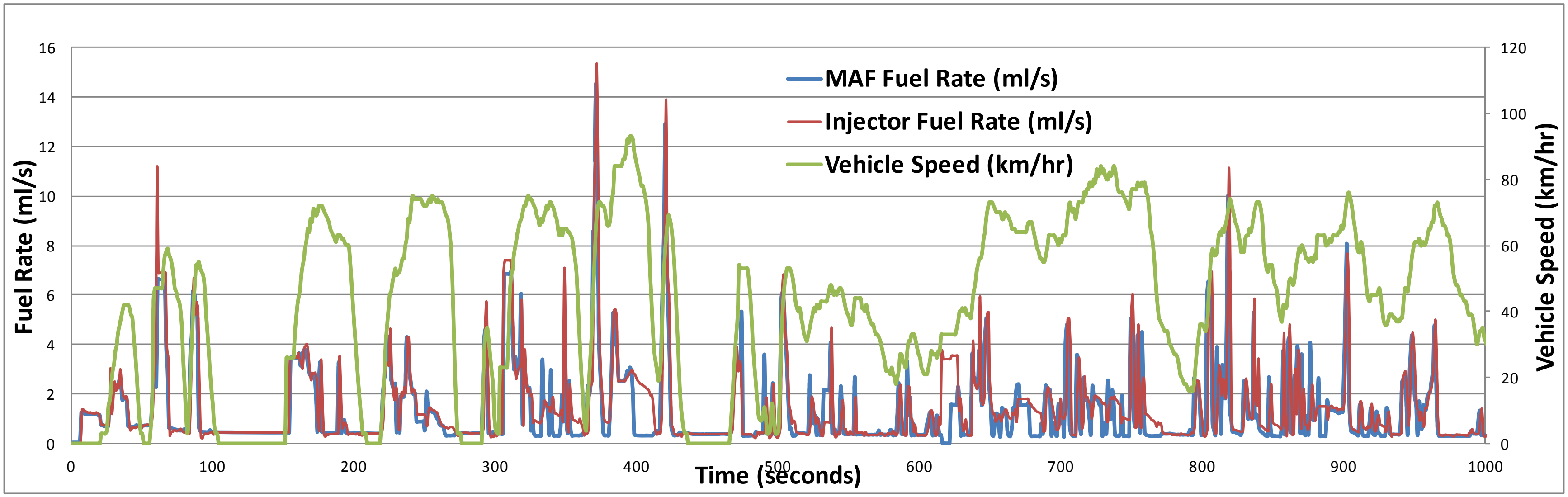
After doing this subsetting of the data, there were only about 1,000 seconds of vehicle operation left for 14 of the 19 vehicles (5 vehicles did not have any open loop start operation points). Plots of the ratio of the OBD-calculated fuel flow to PEMS-measured fuel flow versus OBD parameters that might be associated with enrichment operation: throttle position, acceleration, engine load, and ambient temperature. None of the plots produced any convincing trends that would explain large disagreements between PEMS and OBD fuel flow. Part of the reason that we did not see a convincing trend was that the data was sparse with the 1,000 seconds of data dispersed among 14 test vehicles.

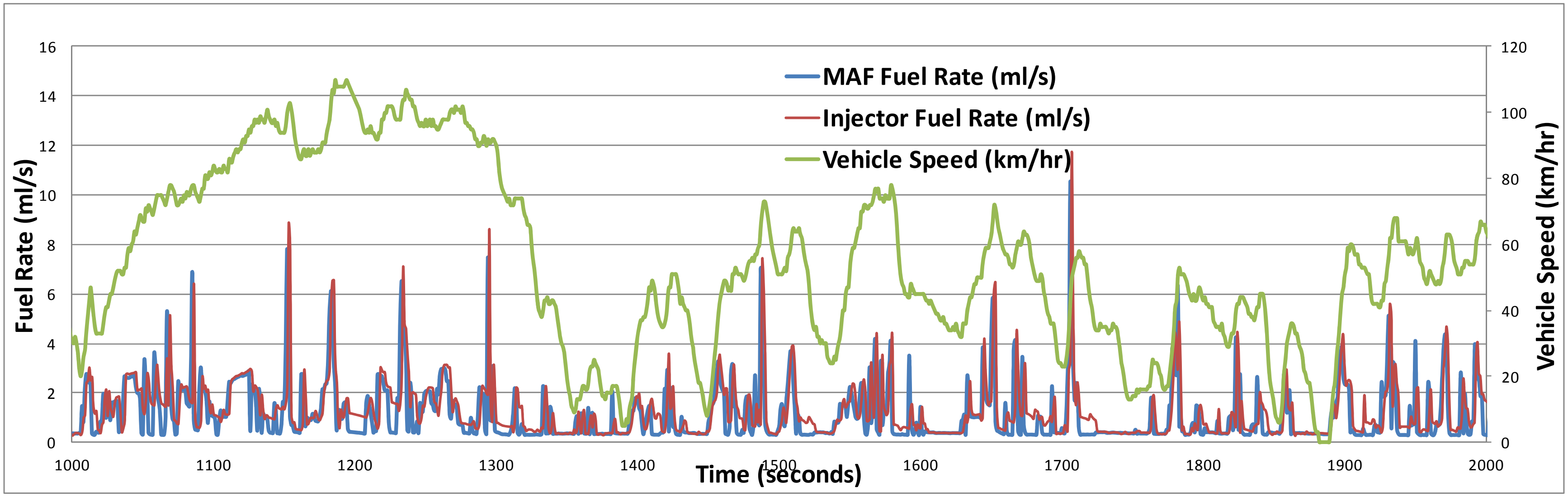
5.5.2 Standard SAE J1979 PID vs. OEM-Enhanced PID Validation

HEM Data provided ERG paired standard SAE J1979 OBDII data along with fuel injector volume (an enhanced PID) data collected from a 2012 Toyota Camry with a 2.5L 4-cylinder engine equipped with a mass air flow sensor and a wide-band oxygen sensor. Specifically, this PID is reported as the volume (mL) of one cylinder's last 10 injections. HEM Data converted this value to a second-by-second fuel rate by multiplying by the number of cylinders, multiplying by the RPM/(2*10) (2 since it's a 4-stroke and "10" because of the prior "10 injection" cumulative), and converting minutes to seconds. Therefore, at engine speeds greater than 600 rpm, this calculation methodology assumes the total fuel consumed over the last second of operation is proportional to the last 10 injections, which will incur an error. Approximately 53 minutes of on-road driving data was collected for a 2012 Toyota Camry, including a “cold start”, although the coolant and ambient temperatures were 23C and 25C at startup and the engine transitioned to closed loop nearly immediately after the vehicle was turned on (and before driving). ERG was not able to obtain additional cold-start or high-throttle enrichment data beyond what was originally provided for this analysis. In addition, HEM Data also provided to ERG 14 minutes of similarly paired data from a 2011 Toyota Prius with a mass air flow sensor and a wide-band oxygen sensor. For both these vehicles, ERG compared the fuel consumption calculated using each vehicle’s mass air flow sensor and wide-band oxygen sensor with the fuel injector-based fuel consumption rate provided by HEM Data. Since these vehicles were equipped with wide-band oxygen sensors, no narrow-band oxygen sensor data was available for this analysis. However, ERG also compared fuel economy using mass air flow sensor data and assuming stoichiometric combustion with fuel injector-based fuel consumption rates provided by the HEM Data datalogger. This latter comparison was performed to provide an estimate of accuracy that might be obtainable with these vehicles if they were narrow-band / MAF vehicles.

2012 Toyota Camry comparison – Figures 5-4(a) – (c) show time-series plot comparisons of the fuel consumption (mL/s) calculated using the Toyota Camry's mass air flow sensor and wide-band oxygen sensor with the fuel-injector-based fuel consumption rate provided by HEM Data. These plots present the full 53 minutes of operation, broken into roughly 17-minute segments. The fuel-injector fuel rate was calculated by HEM Data as previously described. Figure 5-5 shows a parity plot which compares the fuel rate computed using MAF and wide-band oxygen sensor air/fuel ratio (x-axis) with the injector fuel rate (y-axis). On this plot, the 1:1 line is shown in red. Figures 5-6 (a) – (c) and 5-7 show the same data without the wide-band lambda adjustment (as an estimate of results that might be obtained with a narrow-band oxygen sensor for this vehicle). Figures 5-8 and 5-9 provide a comparison between the corrected (with lambda) and the uncorrected (no lambda) fuel rates calculated with mass air flow for the 2012 Toyota Camry.

Figure 5-4 (a)-(c). MAF and Injector Fuel Rate Comparison (with Lambda Adjustment) for 2012 Camry





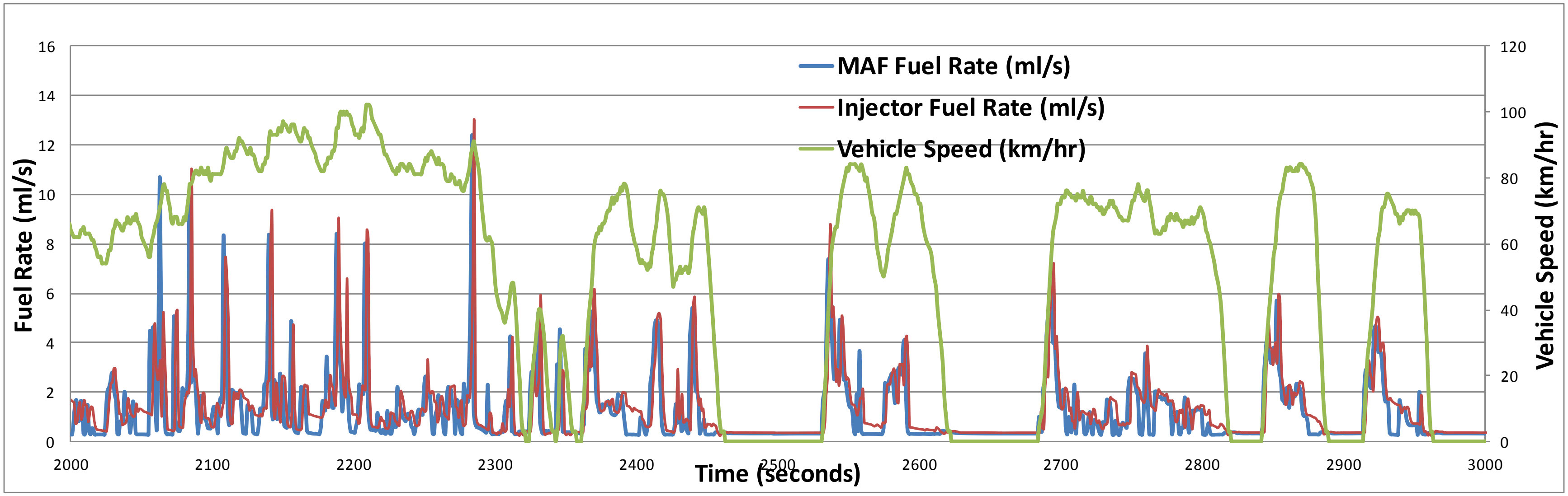


Figure 5-5. MAF-Derived (with Lambda Adjustment) vs. Injector Fuel Rates for 2012 Camry

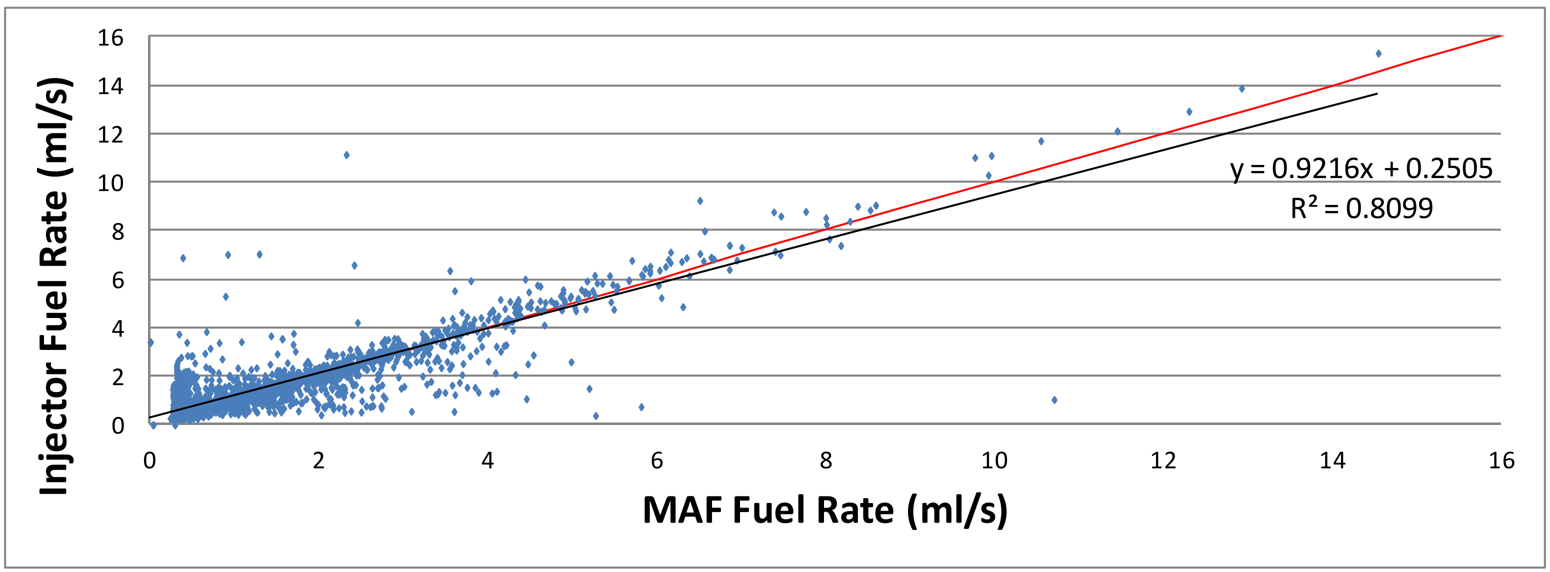
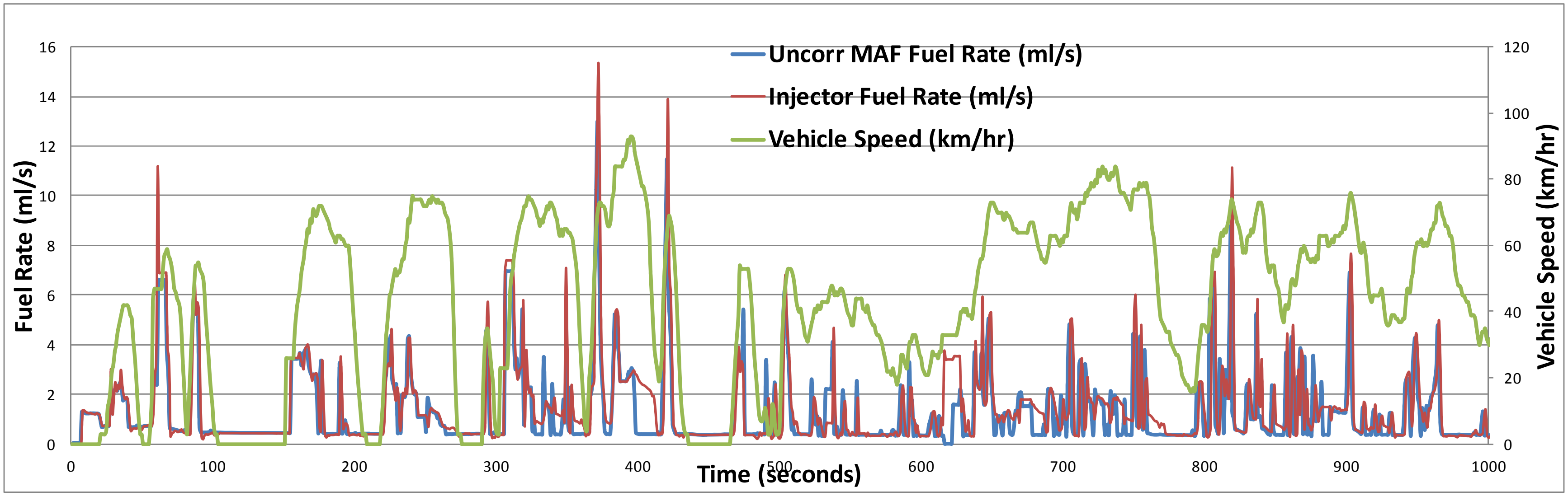
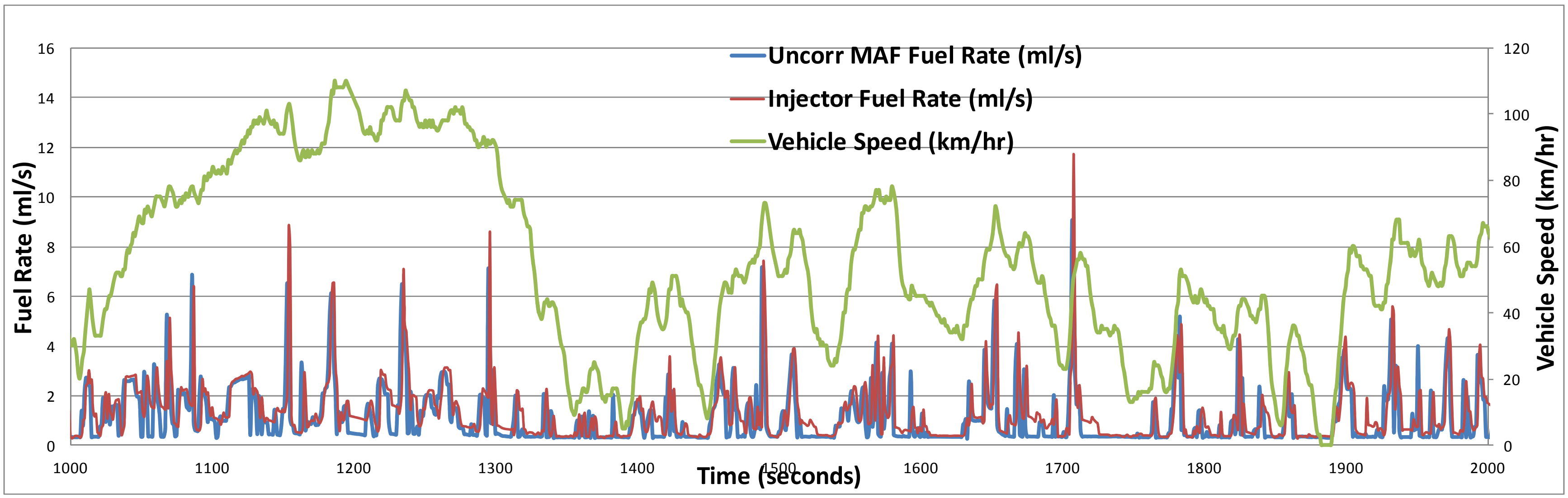


Figure 5-6(a)-(c). MAF and Injector Fuel Rate Comparison (without Lambda Adjustment) for 2012 Camry





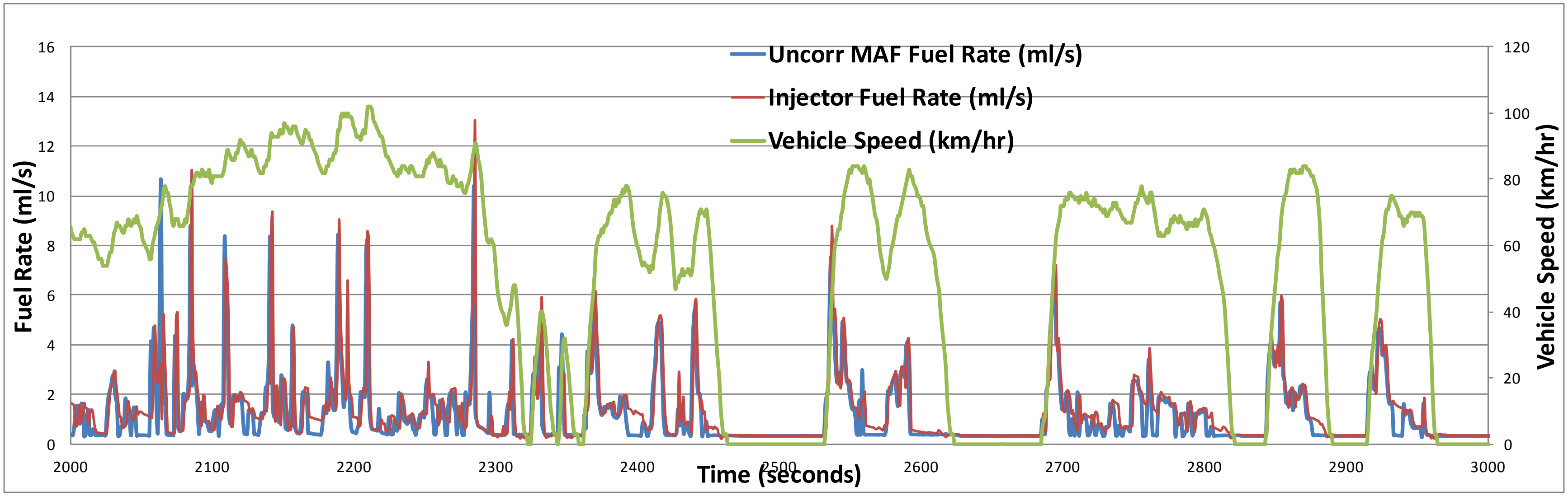


Figure 5-7. MAF-Derived (without Lambda Adjustment) vs. Injector Fuel Rates for 2012 Camry

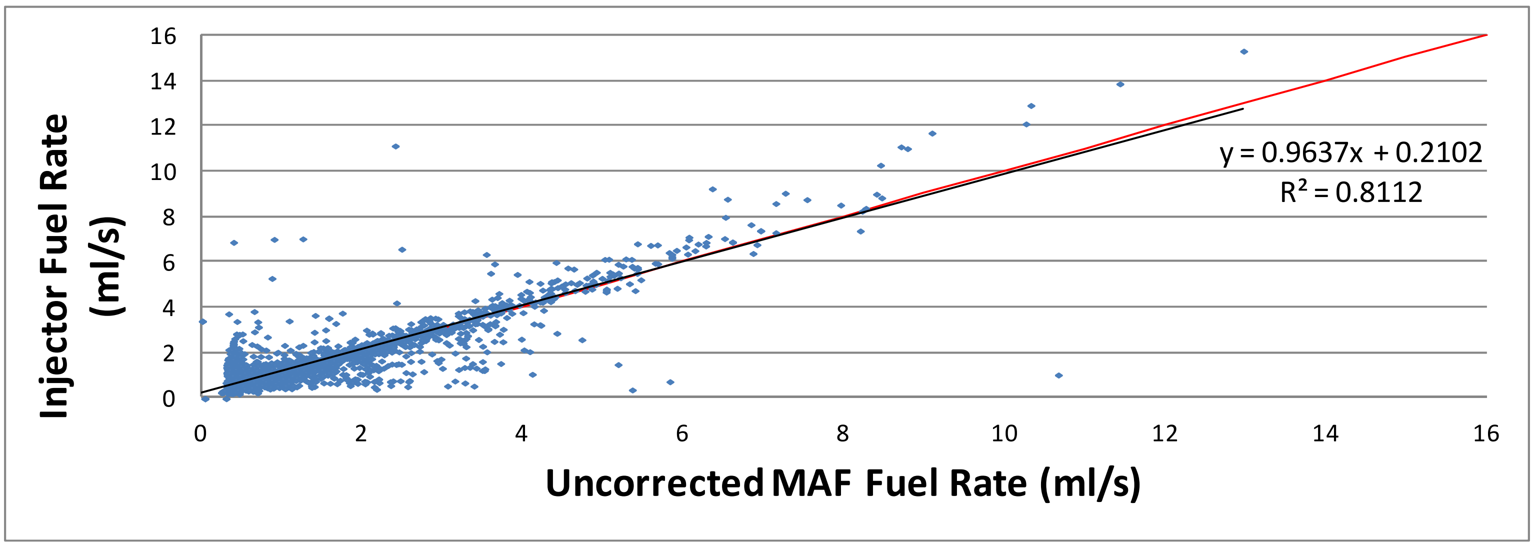
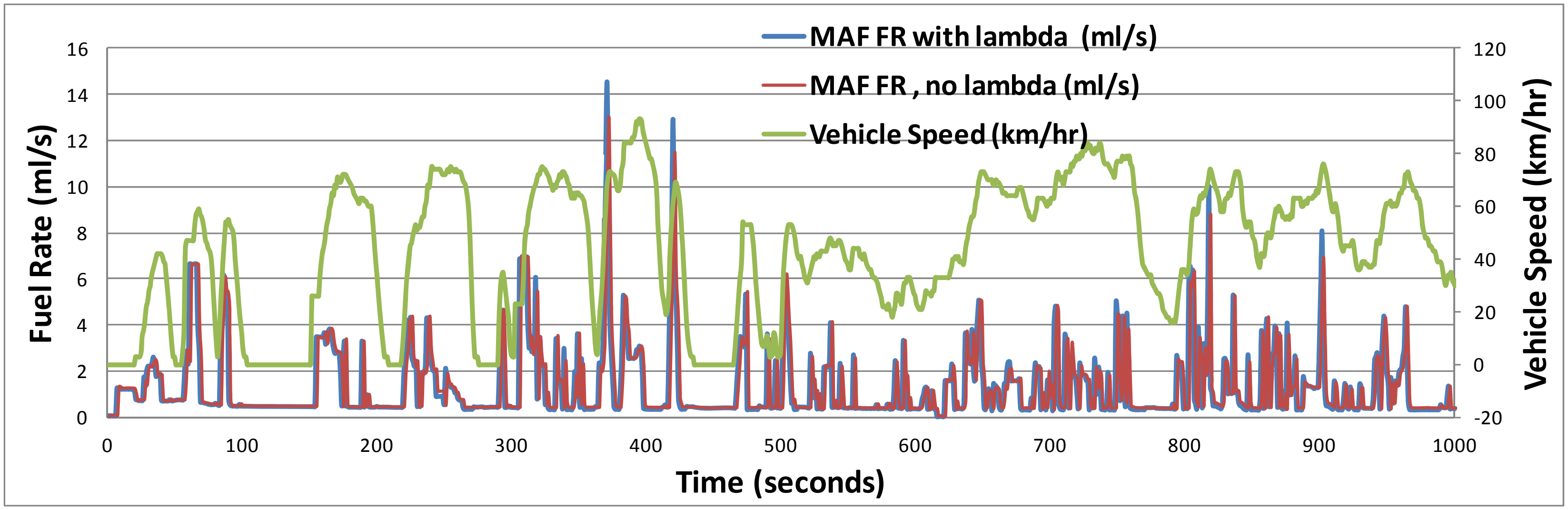
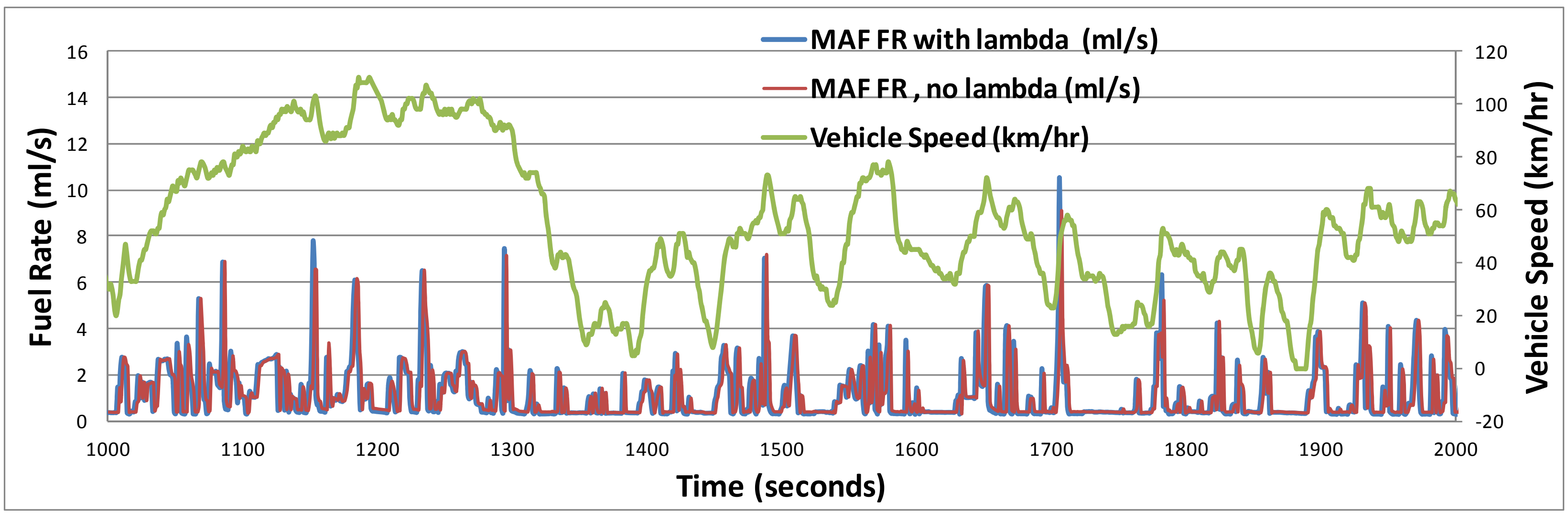


Figure 5-8 (a) – (c). Lambda-Corrected vs. Uncorrected MAF Fuel Rates for 2012 Camry





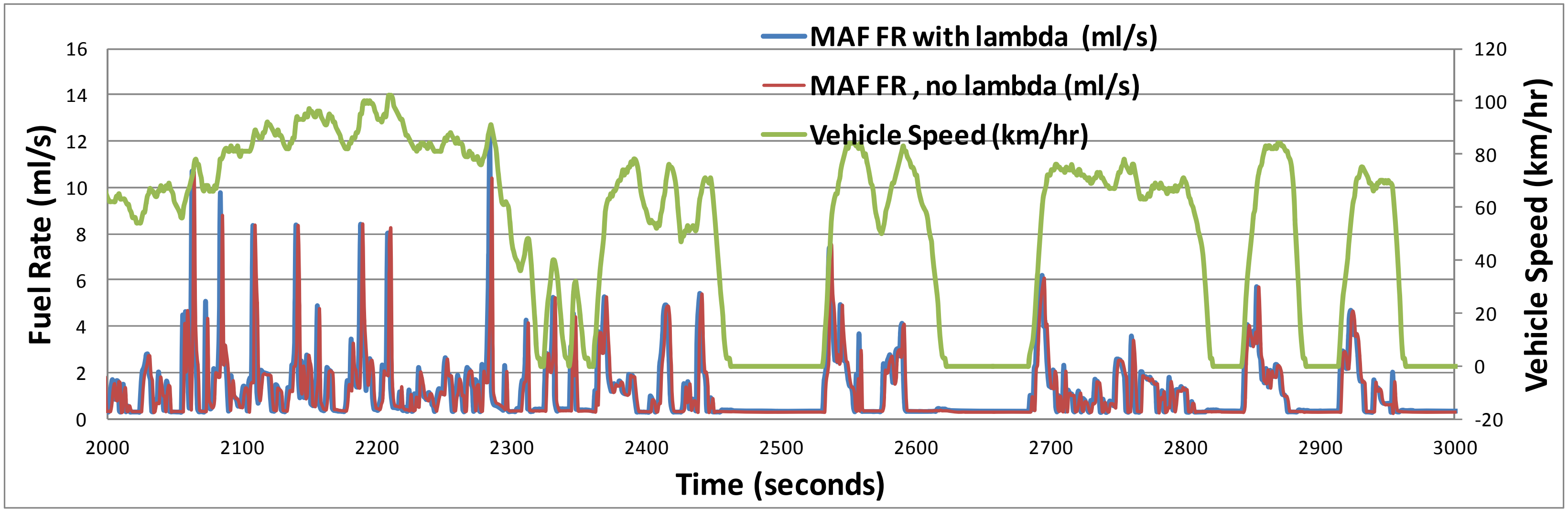


Figure 5-9. Scatter-Plot Comparison of Lambda-Corrected and Uncorrected MAF Fuel Rates for 2012 Camry

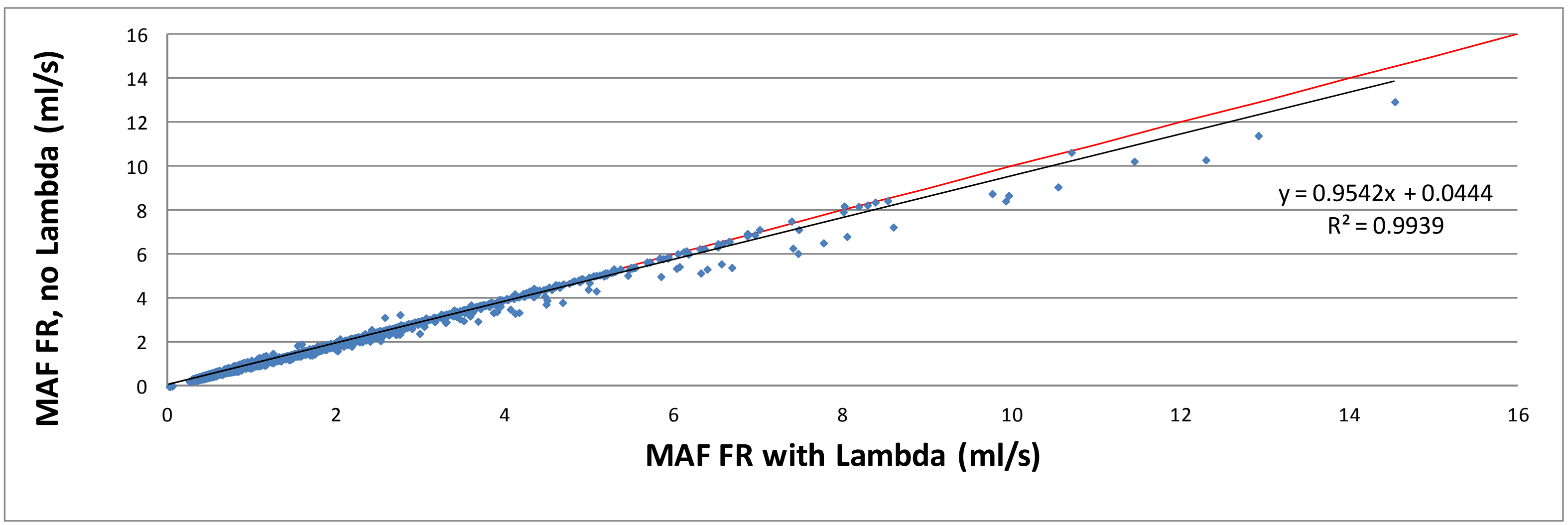


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Table 5-10 summarizes results from the MAF-based fuel rates and the injector-based fuel rates over the 53-minute drive. Values are provided with wide-band oxygen sensor lambda corrections (with λ) and also without the lambda correction (no λ) to provide an estimate of results that would be obtained for a this vehicle if it were equipped with a narrow-band oxygen sensor.

Table 5-10. Comparison of Injector vs. MAF-Based Fuel Consumption Estimates for 2012 Toyota Camry

Parameter	MAF-based value		Injector-based value	Comments
	With λ	No λ		
Cumulative fuel used	3816 mL	3784 mL	4324 mL	Cumulative λ-adjusted MAF fuel rate is 508 mL (13.3%) lower than the injector-based value, the uncorrected is 540 mL (14.3%) lower (using the formula |MAF-FI|/MAF).

As can be seen in Figures 5-4 through 5-7, numerous deviations were seen between MAF-derived fuel rates and the injector-derived fuel rates. As shown in Table 5-11, for the entire test, the average of the differences between the MAF fuel rate (with wide-band oxygen sensor adjustments) and the injector fuel rate was 0.3396 mL/s, the standard deviation of the difference in fuel rates was 0.5631 mL/s, and the maximum difference between the two was 9.6526 mL/s. The average percent difference between the MAF fuel rate and the injector fuel rate was 151%, and the maximum percent difference between the two was 51,385% (injector rate was about 514 times higher than MAF rate). This was during a period when the MAF rate was very near zero but the injector rate was around 3.4 mL/s. This information is summarized in Table 5-11. These values were calculated using the differences between each of the 1 Hz individual data points in the dataset. For this data, the average (cumulative) differences were much smaller than the instantaneous differences (approximately 14% vs. 150%) because these percentages were calculated using absolute values, and the difference of the sums was very different than the average of the individual differences. In this case specifically, the cumulative error estimate (≈14%) is the absolute value of the difference of the cumulative rates, while the instantaneous error estimate (≈150%) is the average of the absolute values of the individual instantaneous fuel rate differences (for each second of operation). For this instantaneous error estimate, each second of operation is weighted equally, and the absolute value of many of these instantaneous errors are quite large (as shown in Table 5-11), since the percentage differences are very large at low flow rates. This effect is eliminated when comparing overall cumulative fuel rates. As an example, consider the values shown in Table 5-12, taken from the Camry data.

Table 5-11. Summary of Differences in MAF-Based and Fuel-Injector-Based Fuel Rates for 2012 Toyota Camry

Parameter	Fuel Rate |MAF – FI|	Relative |MAF-FI|/MAF	Fuel Rate |MAF – FI|	Relative |MAF-FI|/MAF
	With λ Adjustment		Without λ Adjustment	
Average of the differences between 1 Hz MAF-based and injector-based fuel rates	0.3396 mL/s	151 %	0.3292 mL/s	142 %
Standard Deviation of the differences between 1 Hz MAF-based and injector-based fuel rates	0.5631 mL/s	2215 %	0.5610 mL/s	2202 %
Maximum difference between 1 Hz MAF-based and injector-based fuel rates	9.6526 mL/s	51,385 %	9.6255 mL/s	51,084 %
Minimum difference between 1 Hz MAF-based and injector-based fuel rates	0.0 mL/s	0 %	0.0 mL/s	0 %

Table 5-12 Example Illustration of Percentage Differences Between Cumulative and Instantaneous Fuel Rates

Data/Time Stamp	MAF Fuel Rate (mL/s)	Injector Fuel Rate (mL/s)	Absolute Percent Difference
698	0.8341	1.141	37%
699	1.3976	0.9904	29%
700	0.3437	1.0968	219%
701	4.1015	1.3801	66%
702	4.8037	5.0034	4%
703	4.5064	5.062	12%
704	0.6688	3.8401	474%
Cumulative (mL)	16.656	18.514	
Average Instantaneous Percent Difference			120 %
Average Cumulative Percent Difference			11 %

As shown in Tables 5-10 and 5-11, differences exist between the MAF and injector-based fuel rates. Review of regions of the plots in Figure 5-4 (a) – (c) reveals times of operation when these two estimates differ the most. ERG evaluated the MAF-based and injector-based fuel rates to determine the source of the discrepancy. In general, some reasons for these discrepancies could include:

- **Differences in alignment of the signals** – ERG performed an analysis to evaluate alignment of the various signals used in this analysis, and determined that all signals were adequately aligned within 1 Hz (the acquisition rate of this data). However, as the MAF sensor, fuel injector and pre-cat oxygen sensor are at different points in the engine's flow stream, some sub-second misalignment could occur between these three signals and would vary depending on engine speed and flow rate. This would probably be most evident during transient operation.

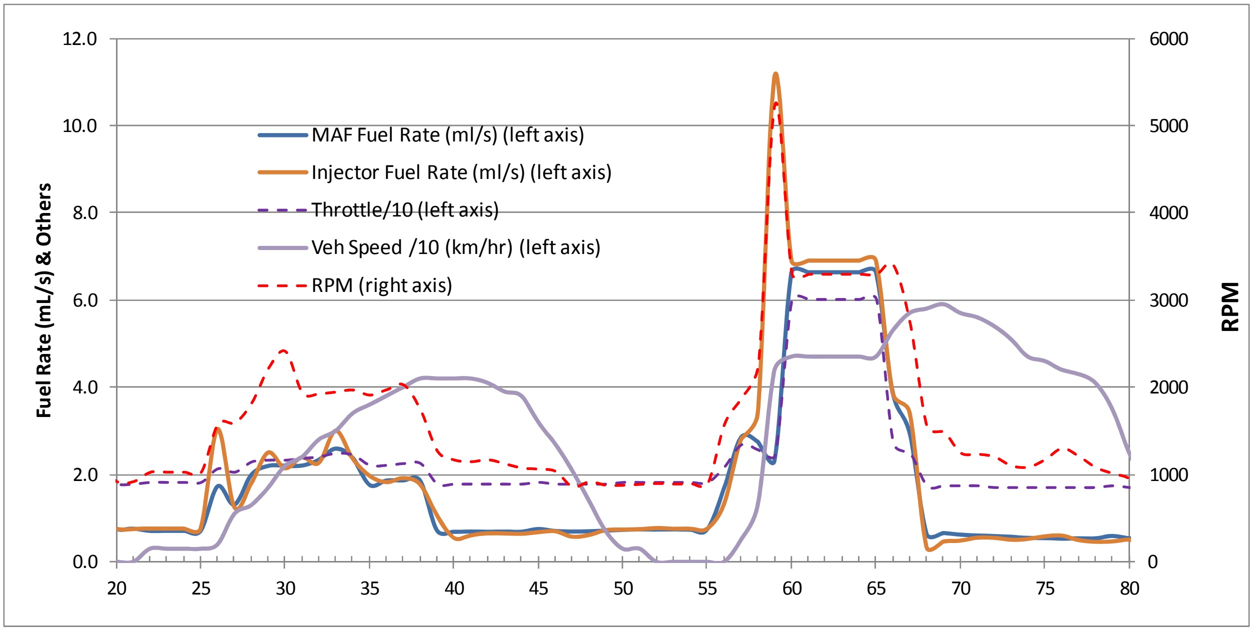
- **Signal and estimation errors** – The OBD variables used for fuel rate determination may have measurement errors, including errors in the measurement of mass air flow by a hot wire anemometer (including the effect of humidity), oxygen content by a wide-band oxygen sensor and even fuel injector flow rate (including injector flow rates that are estimated based on injector durations and fuel system pressures). The signal response rates of various sensors (such as mass airflow sensors and oxygen sensors) will determine the vehicle's ability to capture transient spikes. In addition, using the cumulative of 10 injections for one cylinder to project total flow for all cylinders over one second will produce some error from differences in cylinder flow rates and averaging injection volumes.
- **Differences in system flow and response rates** – In addition to the measurement sensor response rates described above, mass air flow and fuel injector rates will produce very different signals due to how quickly values for these variables can actually change in an engine. Differences in the rate of change in mass air flow vs. injector fuel rate during transients will naturally result in discrepancies between these two variables during periods of acceleration or deceleration. This may be increased when using "10-injection cumulative" for estimating fuel injector rates.

ERG categorized the discrepancies identified in the 53 minutes of Camry data into 5 different types:

- Discrepancy Type 1: Injector fuel rate spike (0.3% of data points)
- Discrepancy Type 2: MAF fuel rate spike (0.4% of data points)
- Discrepancy Type 3: Injector fuel rate higher than MAF fuel rate over multiple points, (13.7% of data points)
- Discrepancy Type 4: Injector fuel rate lower than MAF fuel rate over multiple points (0.2% of data points)
- Discrepancy Type 5: Injector and MAF fuel rates differ during transients (3.0% of data points)

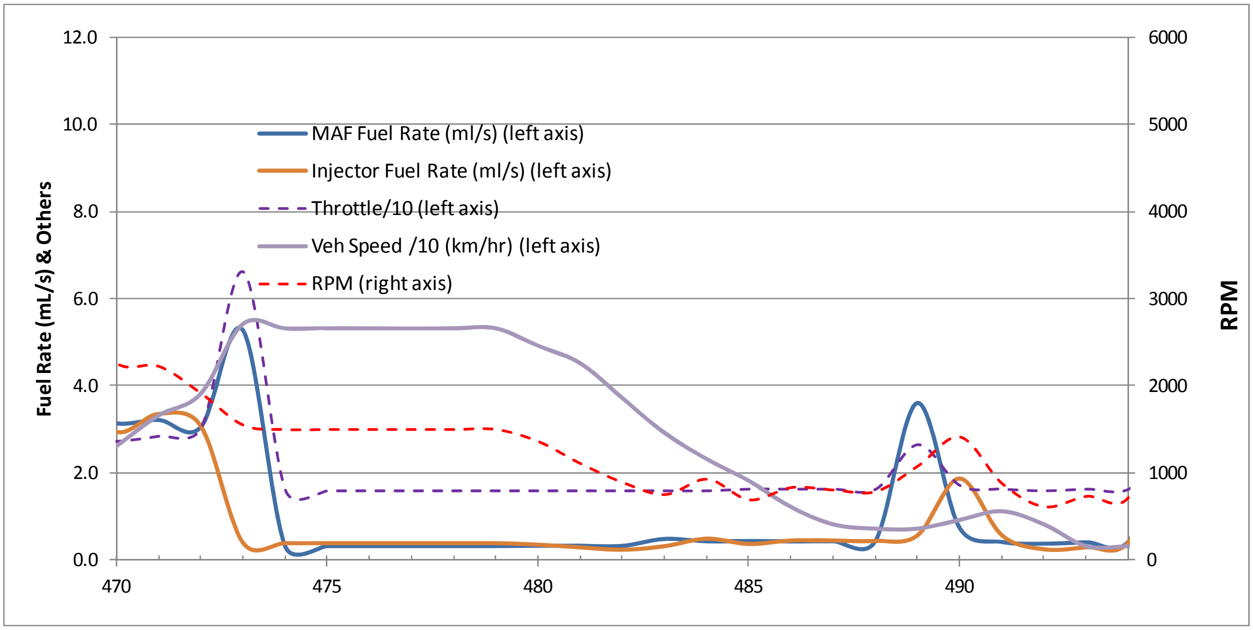
As can be seen, discrepancy type 3 accounts for the majority of discrepancies between the two fuel rates (discrepancy type 3 accounts for nearly 80% of the differences between the two fuel rates). The following are examples of the five different categories of discrepancies seen in the MAF vs. injector fuel rate for the Toyota Camry, including an assessment of the source of error for discrepancy type 3.

Discrepancy Type 1 (Injector fuel rate spike) – This type of discrepancy is a single point (or two) in which the injector- derived fuel rate is much higher than the MAF-derived fuel rate. An example of a few of these points is provided in the plot and table below. As RPM is a factor in the calculation of injector fuel rate, the RPM line does track the injector fuel rate line. ERG did not pinpoint the source of this discrepancy, although the same phenomenon causing discrepancy type 3 could be responsible for discrepancy type 1.



Time (s)	RPM (rpm)	Speed (km/hr)	Load (%)	Throttle (%)	MAF (g/s)	Lambda	MAF Fuel Rate (mL/s)	Injector Fuel Rate (mL/s)	Discrepancy Type
24	1020	3	34	18	7.6	1.04	0.699	0.749	
25	1020	3	34	18	7.6	1.04	0.699	0.749	
26	**1576**	**4**	**38**	**21**	**16.2**	**0.90**	**1.721**	**3.032**	**1**
27	1586	11	38	20	14.3	1.05	1.300	1.240	
28	1817	13	50	23	21.5	1.03	1.984	1.790	
29	2217	17	42	23	22.9	0.99	2.191	2.495	
30	2405	22	38	23	23.2	1.01	2.195	2.134	
31	1929	24	48	24	22.4	0.97	2.197	2.384	
32	1921	28	46	24	24.3	1.00	2.331	2.257	
33	**1941**	**30**	**53**	**25**	**25.9**	**0.95**	**2.589**	**2.997**	**1**
34	1963	34	51	24	25.0	1.00	2.379	2.361	
…									
56	1571	0	49	22	16.2	0.93	1.665	1.309	
57	1870	5	69	27	30.1	1.01	2.839	2.790	
58	**2253**	**13**	**55**	**25**	**28.6**	**0.99**	**2.746**	**3.389**	**1**
59	**5248**	**44**	**59**	**24**	**25.3**	**1.04**	**2.323**	**11.143**	**1**
60	3292	47	87	60	69.4	1.00	6.638	6.903	
61	3292	47	87	60	69.4	1.00	6.638	6.903	
62	3292	47	87	60	69.4	1.00	6.638	6.903	

Discrepancy Type 2 (MAF fuel rate spike) – This type of discrepancy is just a single point (or two) in which the MAF-derived fuel rate is much higher than the injector-derived fuel rate. An example of this is provided in the plot and table below. As seen in the table, these MAF spikes could be a result of a highly transient throttle “blip” (1-second jump in load and throttle position) not fully captured by the injector fuel rate estimate.



Time (s)	RPM (rpm)	Speed (km/hr)	Load (%)	Throttle (%)	MAF (g/s)	Lambda	MAF Fuel Rate (mL/s)	Injector Fuel Rate (mL/s)	Discrepancy Type
470	2255	26	60	27	32.6	0.99	3.132	2.931	
471	2223	33	62	28	33.7	1.00	3.210	3.341	
472	1912	38	72	30	32.8	1.03	3.044	3.068	
473	**1549**	**54**	**93**	**66**	**56.3**	**1.02**	**5.271**	**0.382**	**2**
474	1500	53	11	16	4.0	1.23	0.312	0.370	
475	1500	53	11	16	4.0	1.23	0.312	0.370	
487	806	8	20	16	4.1	0.92	0.422	0.432	
488	789	7	20	16	4.1	0.92	0.421	0.423	
489	**1083**	**7**	**152**	**26**	**35.6**	**0.94**	**3.598**	**0.549**	**2**
490	1413	9	25	17	7.7	1.01	0.728	1.857	
491	878	11	17	16	4.2	0.99	0.405	0.556	

Discrepancy Type 3 (Injector higher than MAF over multiple points) – Discrepancy type 3 was typically characterized by the injector fuel rate failing to track a drop in the MAF fuel rate, as shown in the plot and table below. Discrepancy type 3 deviations dominated the differences between MAF and injector fuel rates (nearly 80% of the differences between the two fuel rates were discrepancy type 3). Also, these deviations appeared to be systematic bias, rather than spurious points (such as MAF or injector fuel rate spikes) or delays during transients possibly due to signal rise and fall rates.

During discrepancy type 3 deviations, nearly all (89%) of the observations occurred at throttle positions of less than 17%. The minimim throttle position seen in our data was 15%, so this is essentially a closed throttle, which could indicate an inaccuracy in the data being reported from the OBD system, or this could be intentional by the vehicle manufacturer to represent throttle required for engine operation (including accessory loads) without accelerator pedal depression. SAE J1979 states "Throttle position at idle usually indicates greater than 0%, and throttle position at wide open throttle usually indicates less than 100%"[42]. During these times with type 3 discrepancies, the following was observed:

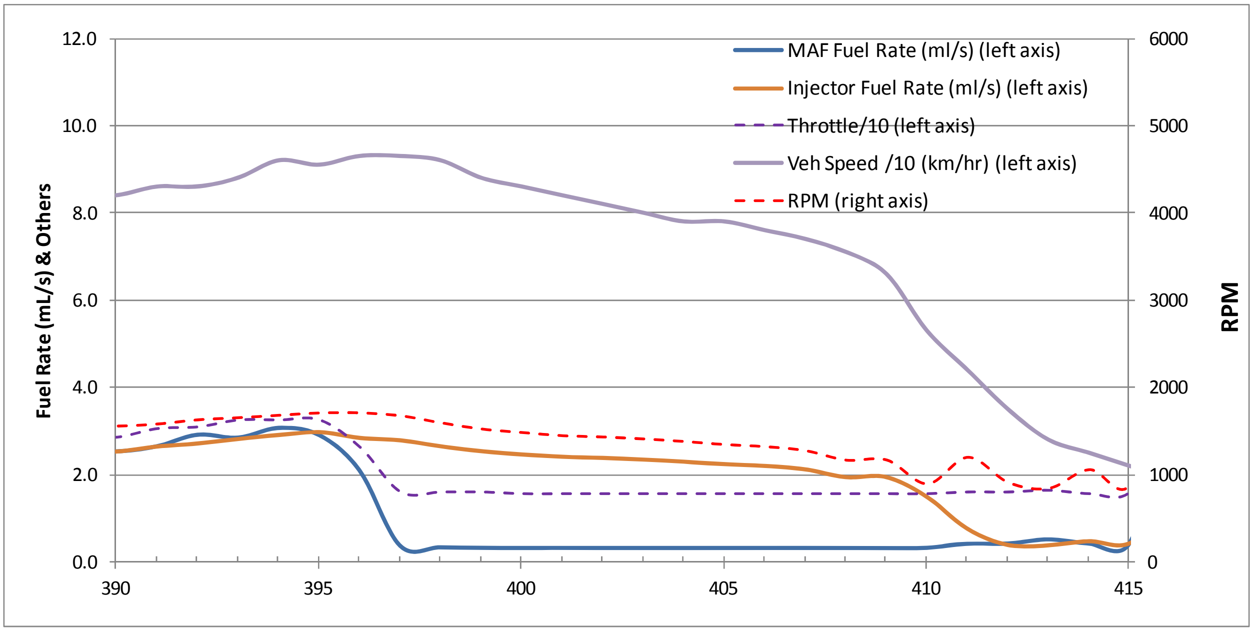
- Throttle was usually less than 17%, indicating the throttle was closed
- The average mass air flow was 4 g/s
- The average lambda was 1.2 - this lean air/fuel ratio supports that the throttle was closed, as lean air/fuel mixtures generally only occur during deceleration fuel cut
- The average calculated injector fuel rate was 0.9915 mL/s
- The vehicle was cruising at a steady speed or decelerating (average speed of 40 miles/hour) at low load (average load of 12%) and at a low engine speed (average engine speed less than 1400 rpm).

Since exhaust data was not available to evaluate the accuracy of the MAF-based or injector-based fuel rates, engineering judgment was used to assess whether the MAF fuel rate or the injector fuel rate appeared most reasonable. The average mass air flow during the entire 53-minute test (including during times when injector fuel rate and the MAF fuel rate agree) when the throttle was under 17% was 4.0 g/s. Stoichiometric combustion of 4 g/s of air corresponds to 0.3812 mL/s of E10 (with an A/F ratio of 14.08 and a fuel specific gravity of 0.745), or 0.3177 mL/s of E10 if combusting at a lambda of 1.2.

In order to obtain a stoichiometric fuel rate of 0.9915 mL/s (the injector fuel rate seen during condition 3 with a throttle position under 17%), a mass air flow rate of 11 g/s would be required, and at a lambda of 1.2, a mass air flow rate of nearly 13 g/s would be required. No mass air flow rates near these values were seen anywhere in the test at throttle position less than 17% (our data showed an average throttle position of 20% at an average load of 30% for mass air flow rates between 11 and 13 g/s). Also, since the maximum mass air flow rate is physically limited due to the closed throttle plates, we believe a mass air flow of approximately 4 g/s at a throttle position of under 17 % to be reasonable. We also believe the lambda output of the wide-band oxygen sensor to be reasonable since the oxygen sensor is independently monitored by the OBD system. A fuel rate of 0.9915 mL/s for E10 fuel with a 4 g/s mass air flow rate corresponds to a lambda value of 0.38 (air /fuel ratio of 5.35), which is much lower than typical vehicle operation and could illuminate the malfunction indicator light and possibly result in vehicle

[42] SAE J1979 Revised February 2012, Section 3.1.1., www.sae.org

drivability problems. Because of these reasons, we feel the injector-based fuel rate may be incorrect during these discrepancies.

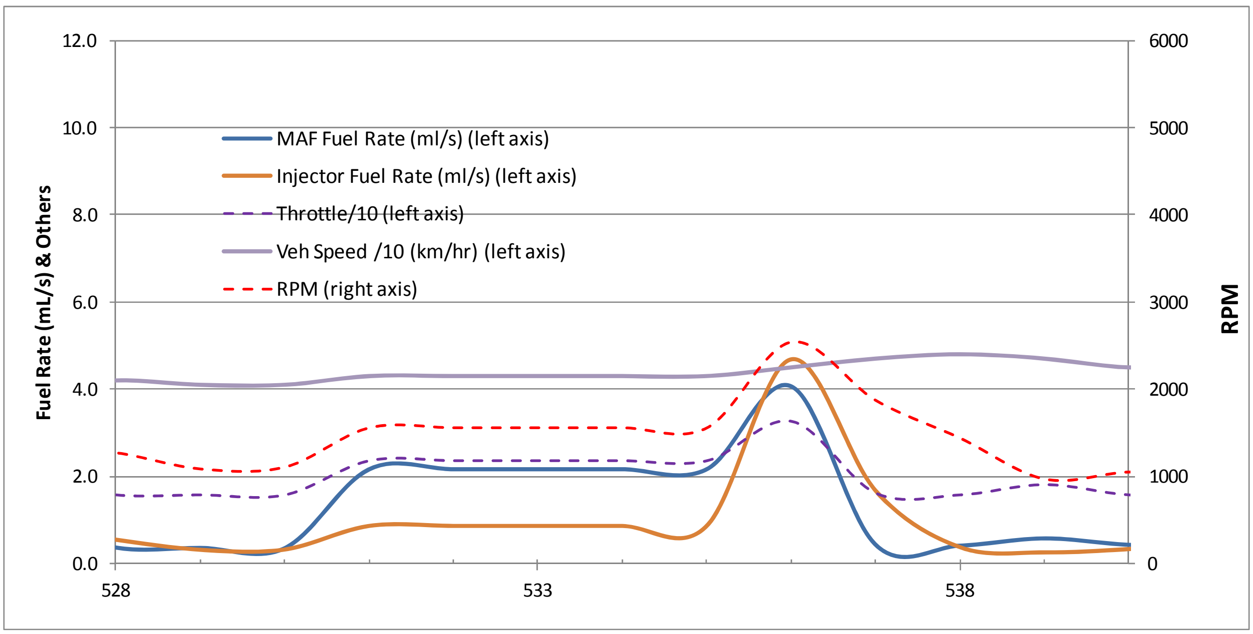


In discussions regarding this discrepancy, HEM Data was unable to identify the source of the poor correlation, but did indicate that the relationship between the MAF and calculated injector fuel rate varies among vehicle types. Although ERG believes the injector fuel rate is suspect during these deviations, neither ERG nor HEM Data were able to further identify why the injector fuel rate could be in error, beyond that previously described. Section 5.6.6 of this report describes additional analysis which could be performed to futher explore the source of this discrepancy. Additional investigation of this discrepancy is recommended prior to proceeding with a study in which enhanced PIDs are collected.

Time (s)	RPM (rpm)	Speed (km/hr)	Load (%)	Throttle (%)	MAF (g/s)	Lambda	MAF Fuel Rate (mL/s)	Injector Fuel Rate (mL/s)	Discrepancy Type
395	1706	91	74	33	30.6	1.00	2.910	2.972	
396	**1708**	**93**	**63**	**26**	**21.8**	**0.99**	**2.095**	**2.839**	**3**
397	**1674**	**93**	**11**	**16**	**4.8**	**1.23**	**0.368**	**2.783**	**3**
398	**1593**	**92**	**11**	**16**	**4.3**	**1.23**	**0.333**	**2.648**	**3**
399	**1523**	**88**	**11**	**16**	**4.2**	**1.23**	**0.321**	**2.531**	**3**
400	**1482**	**86**	**11**	**16**	**4.1**	**1.23**	**0.316**	**2.464**	**3**
401	**1446**	**84**	**11**	**16**	**4.1**	**1.23**	**0.320**	**2.404**	**3**
402	**1431**	**82**	**11**	**16**	**4.1**	**1.23**	**0.316**	**2.379**	**3**
403	**1409**	**80**	**12**	**16**	**4.1**	**1.23**	**0.317**	**2.342**	**3**
404	**1380**	**78**	**12**	**16**	**4.1**	**1.23**	**0.316**	**2.293**	**3**
405	**1345**	**78**	**12**	**16**	**4.1**	**1.23**	**0.319**	**2.235**	**3**
406	**1320**	**76**	**13**	**16**	**4.1**	**1.23**	**0.317**	**2.195**	**3**

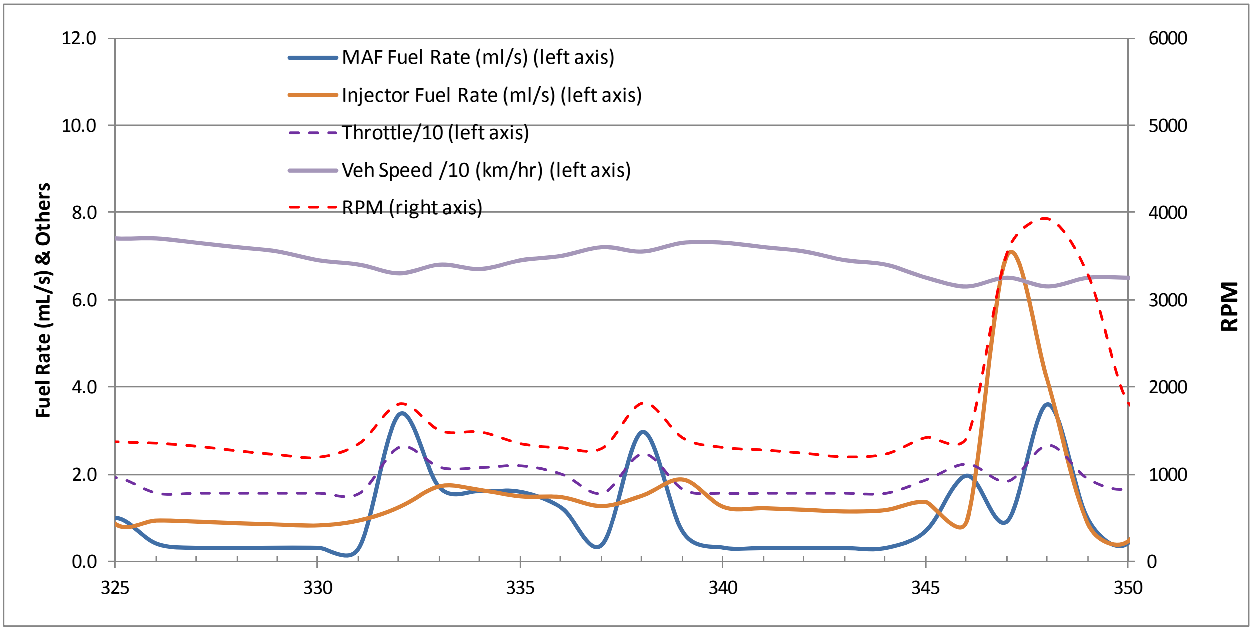
Time (s)	RPM (rpm)	Speed (km/hr)	Load (%)	Throttle (%)	MAF (g/s)	Lambda	MAF Fuel Rate (mL/s)	Injector Fuel Rate (mL/s)	Discrepancy Type
407	**1273**	**74**	**13**	**16**	**4.1**	**1.23**	**0.317**	**2.117**	**3**
408	**1166**	**71**	**14**	**16**	**4.1**	**1.23**	**0.317**	**1.938**	**3**
409	**1166**	**66**	**14**	**16**	**4.1**	**1.23**	**0.317**	**1.939**	**3**
410	**894**	**53**	**18**	**16**	**4.2**	**1.23**	**0.323**	**1.486**	**3**
411	**1198**	**44**	**14**	**16**	**4.1**	**0.94**	**0.415**	**0.753**	**3**
412	909	35	18	16	4.1	0.93	0.419	0.381	

Discrepancy Type 4 (Injector lower than MAF over multiple points) – This discrepancy was very infrequent, and is shown in the plot and table below. As shown in the table, load, throttle position, and MAF all increase during this period of discrepancy. Injector fuel rate and RPM also increase, but not as much as the other parameters.



Time (s)	RPM (rpm)	Speed (km/hr)	Load (%)	Throttle (%)	MAF (g/s)	Lambda	MAF Fuel Rate (mL/s)	Injector Fuel Rate (mL/s)	Discrepancy Type
530	1102	41	13	16	3.5	1.00	0.337	0.316	
531	**1552**	**43**	**51**	**24**	**23.1**	**1.02**	**2.153**	**0.857**	**4**
532	**1552**	**43**	**51**	**24**	**23.1**	**1.02**	**2.153**	**0.857**	**4**
533	**1552**	**43**	**51**	**24**	**23.1**	**1.02**	**2.153**	**0.857**	**4**
534	**1552**	**43**	**51**	**24**	**23.1**	**1.02**	**2.153**	**0.857**	**4**
535	**1552**	**43**	**51**	**24**	**23.1**	**1.02**	**2.153**	**0.857**	**4**
536	2537	45	70	33	42.8	1.00	4.060	4.684	
537	1866	47	9	16	4.3	0.98	0.418	1.667	
538	1433	48	13	16	4.1	0.98	0.398	0.369	
539	963	47	20	18	7.3	1.23	0.564	0.248	
540	1045	45	15	16	3.9	0.90	0.417	0.326	

Discrepancy Type 5 (Signals differ during transients, combination of types 1-4) – This discrepancy could actually be considered to be a combination of discrepancy types 1 through 4 listed above, occurring back-to-back over multiple points. Typically, this appears as an injector which fails to track multiple rapid MAF transients. The table below lists the alternate discrepancy types (1 through 4) which could be assigned to each data point.



Time (s)	RPM (rpm)	Speed (km/hr)	Load (%)	Throttle (%)	MAF (g/s)	Lambda	MAF Fuel Rate (mL/s)	Injector Fuel Rate (mL/s)	Discrepancy Type
325	**1370**	**74**	**32**	**19**	**10.9**	**1.04**	**1.000**	**0.840**	**5 (3)**
326	**1355**	**74**	**13**	**16**	**4.3**	**0.99**	**0.408**	**0.930**	**5 (3)**
327	**1319**	**73**	**12**	**16**	**4.0**	**1.23**	**0.310**	**0.906**	**5 (3)**
328	**1266**	**72**	**13**	**16**	**4.0**	**1.23**	**0.309**	**0.870**	**5 (3)**
329	**1222**	**71**	**13**	**16**	**4.0**	**1.23**	**0.309**	**0.839**	**5 (3)**
330	**1194**	**69**	**13**	**16**	**4.0**	**1.23**	**0.310**	**0.820**	**5 (3)**
331	**1355**	**68**	**11**	**16**	**4.0**	**1.23**	**0.309**	**0.931**	**5 (3)**
332	**1806**	**66**	**90**	**26**	**36.7**	**1.03**	**3.377**	**1.241**	**5 (2)**
333	**1497**	**68**	**44**	**22**	**16.5**	**0.93**	**1.686**	**1.720**	**5 (2)**
334	**1482**	**67**	**45**	**22**	**16.7**	**0.98**	**1.615**	**1.631**	**5 (2)**
335	1347	69	49	22	16.5	0.99	1.594	1.486	
336	**1302**	**70**	**40**	**20**	**12.8**	**0.99**	**1.229**	**1.468**	**5 (3)**
337	**1301**	**72**	**12**	**16**	**4.0**	**1.00**	**0.383**	**1.264**	**5 (3)**
338	1816	71	61	25	25.4	0.81	2.971	1.506	
339	**1409**	**73**	**24**	**16**	**6.7**	**0.96**	**0.666**	**1.872**	**5 (3)**
340	**1305**	**73**	**13**	**16**	**4.1**	**1.23**	**0.314**	**1.241**	**5 (3)**
341	**1276**	**72**	**13**	**16**	**4.0**	**1.23**	**0.309**	**1.214**	**5 (3)**
342	**1238**	**71**	**13**	**16**	**4.0**	**1.23**	**0.308**	**1.178**	**5 (3)**
343	**1198**	**69**	**13**	**16**	**4.0**	**1.23**	**0.306**	**1.140**	**5 (3)**
344	**1232**	**68**	**14**	**16**	**4.0**	**1.23**	**0.308**	**1.172**	**5 (3)**
345	**1422**	**65**	**23**	**19**	**9.2**	**1.23**	**0.708**	**1.353**	**5 (3)**
346	**1433**	**63**	**52**	**22**	**18.8**	**0.91**	**1.967**	**0.917**	**5 (2)**
347	**3564**	**65**	**12**	**18**	**9.5**	**0.98**	**0.921**	**7.024**	**5 (1)**
348	**3927**	**63**	**40**	**27**	**38.0**	**1.00**	**3.605**	**4.115**	**5 (1)**
349	**3260**	**65**	**11**	**19**	**9.6**	**0.96**	**0.956**	**0.838**	**5 (1)**
350	1800	65	11	17	5.6	1.23	0.431	0.463	

Toyota Prius comparison – Figure 5-10 shows a time-series plot comparison of the fuel consumption (mL/s) calculated using the Toyota Prius' mass air flow sensor and wide-band oxygen sensor data with the fuel-injector-based fuel rate provided by HEM Data. Figure 5-11 shows a parity plot which compares the fuel rate computed using MAF and wide-band oxygen sensor (x-axis) with the injector fuel rate (y-axis). On this plot, the 1:1 line is shown in red. As can be seen in Figure 5-11, the correlation between the hybrid Prius injector vs. MAF fuel rates was much better than for the conventional (non-hybrid) Camry. Figures 5-12 and 5-13 show the same data without the wide-band lambda adjustment (as an estimate of results that might be obtained with a narrow-band oxygen sensor). Figures 5-14 and 5-15 provide a comparison between the corrected (with lambda) and uncorrected (no lambda) fuel rates calculated with mass air flow for the 2011 Toyota Prius.

Figure 5-10. Comparison of MAF-Derived (with Lambda Adjustment) and Injector Fuel Rates for 2011 Prius

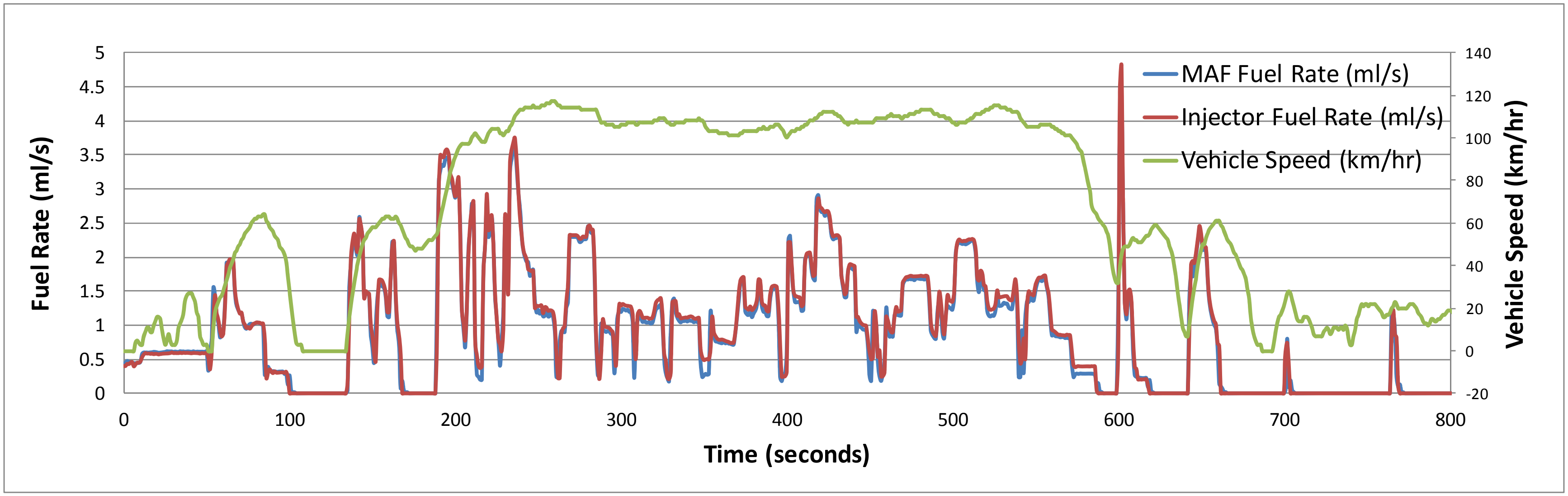


Figure 5-11. MAF-Derived (with Lambda Adjustment) vs. Injector Fuel Rates for 2011 Prius

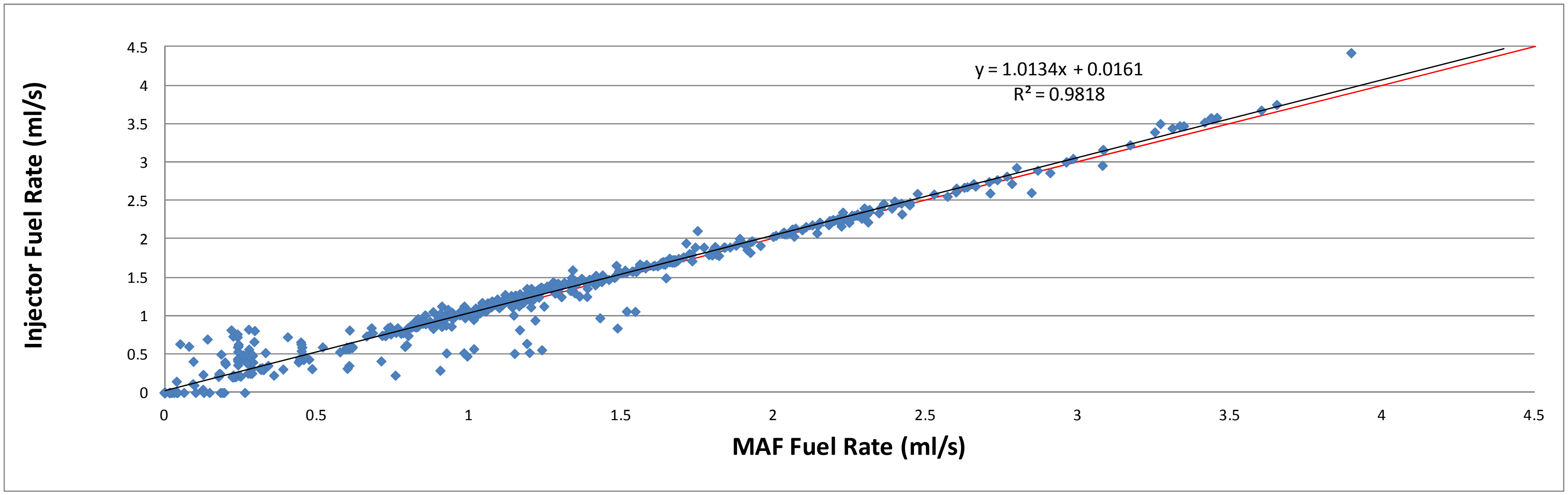


Figure 5-12. Comparison of MAF-Derived (without Lambda Adjustment) and Injector Fuel Rates for 2011 Prius

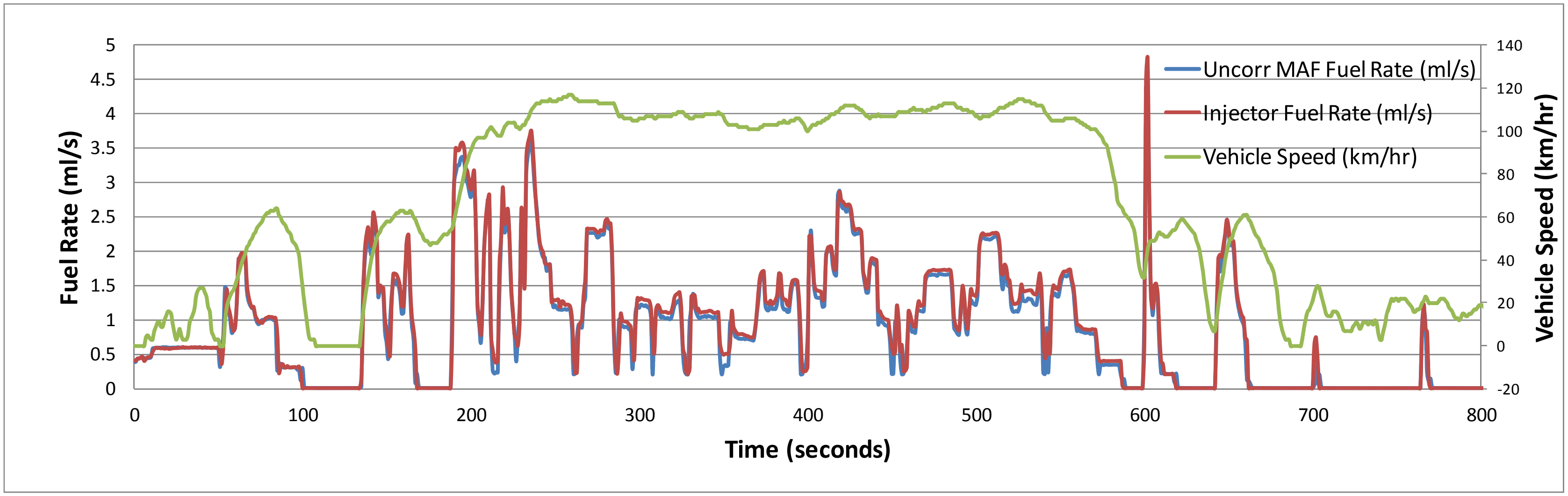


Figure 5-13. MAF-Derived (without Lambda Adjustment) vs. Injector Fuel Rates for 2011 Prius

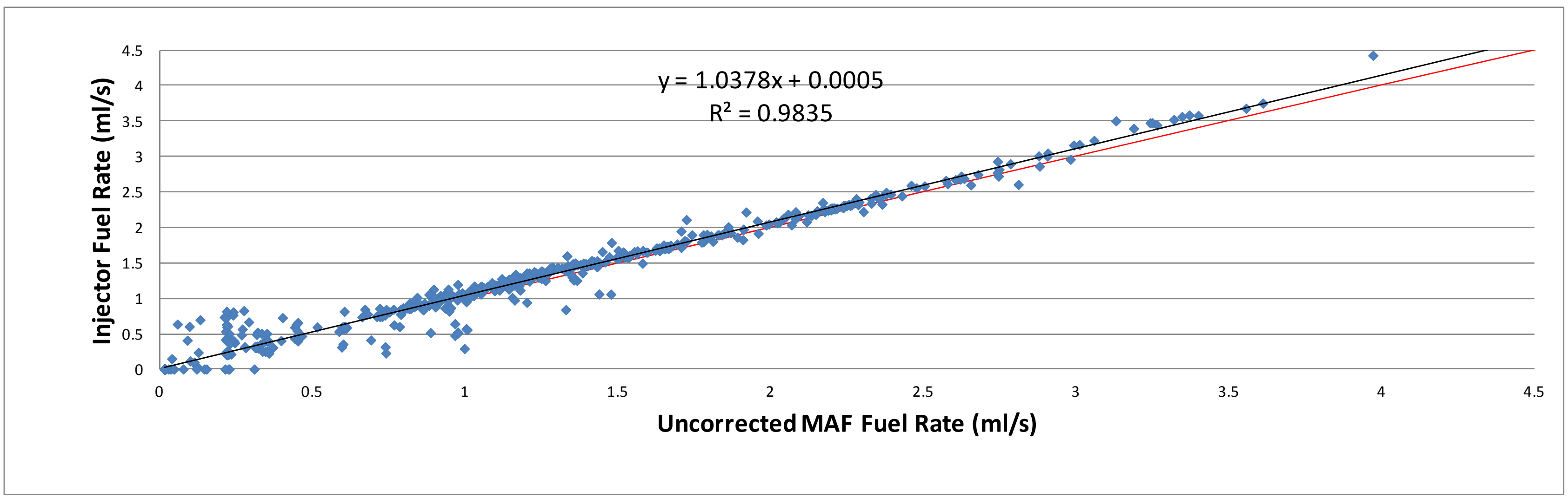


Figure 5-14. Lambda-Corrected vs. Uncorrected MAF Fuel Rates for 2011 Prius

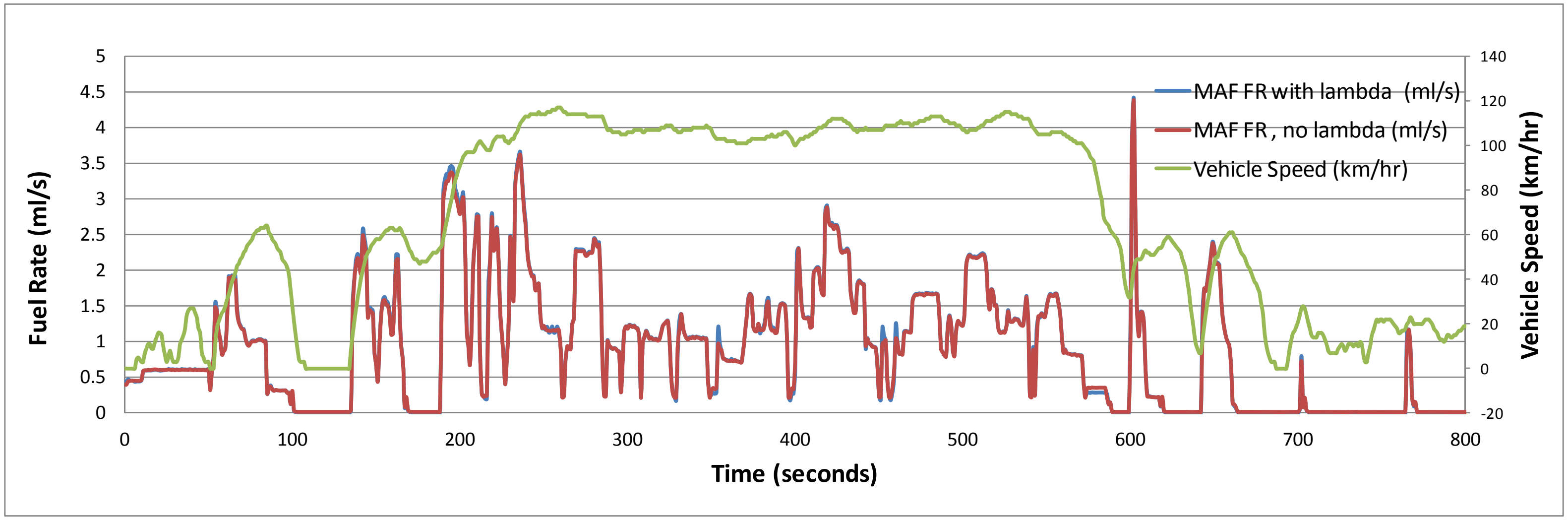


Figure 5-15. Scatter-Plot Comparison of Lambda-Corrected and Uncorrected MAF Fuel Rates for 2011 Prius

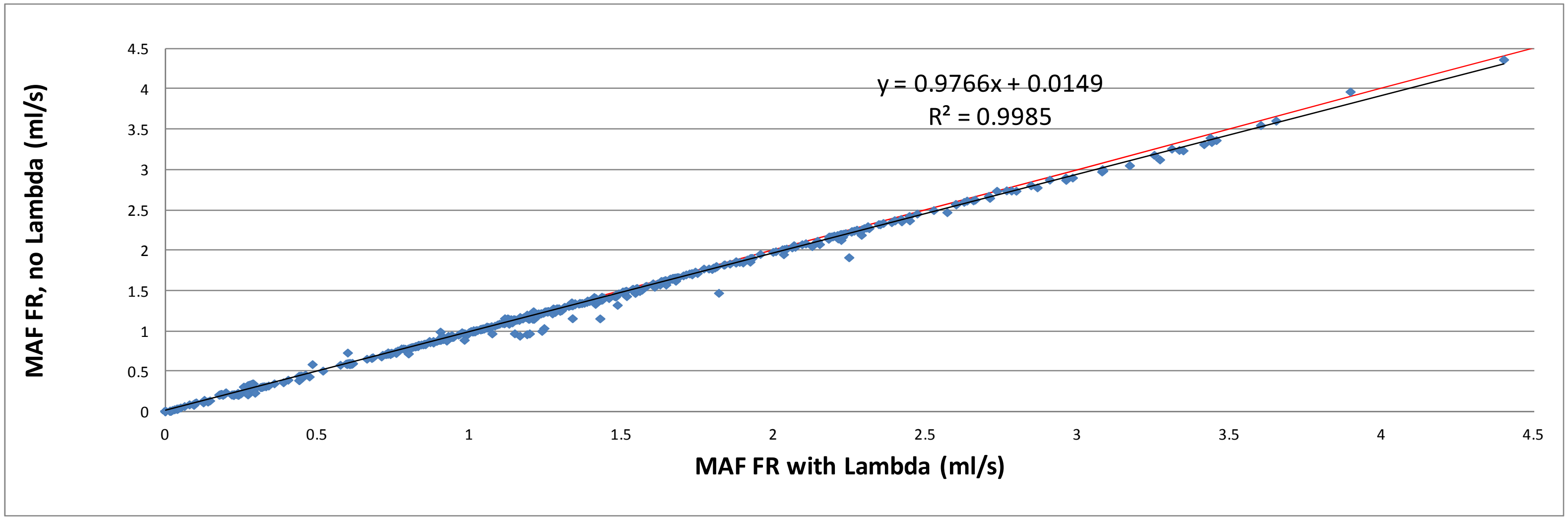


Table 5-13 summarizes results from the MAF-derived fuel rate and the injector-derived fuel rate over the 14-minute drive. Values are provided with wide-band oxygen sensor corrections (with λ) and also without the correction (no λ) to provide an estimate of results that would be obtained for this vehicle if it were equipped with a narrow-band oxygen sensor.

Table 5-13. Comparison of the Toyota Prius' Injector vs. MAF-Based Fuel Consumption Estimates

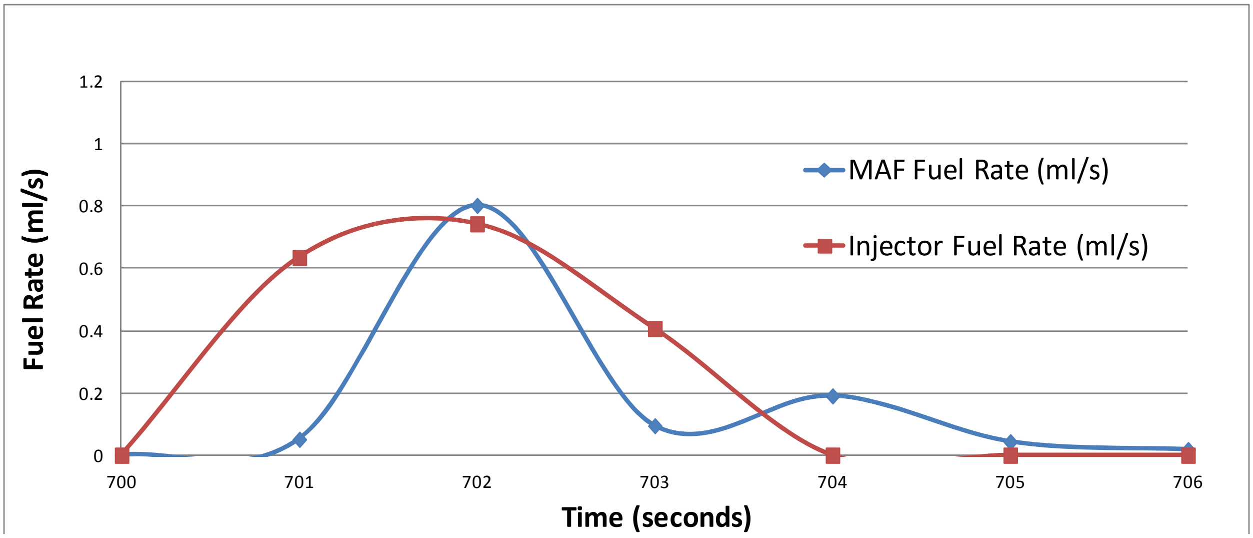
Parameter	MAF-based value		Injector-based value	Comments
	With λ	No λ		
Cumulative fuel used	729 mL	725 mL	753 mL	Cumulative λ-adjusted MAF fuel rate is 24 mL (3.3%) lower than injector-based value, the uncorrected is 28 mL (3.9%) lower (using the formula |MAF-FI|/MAF)

As can be seen in Figures 5-11 and 5-13, most of the scatter between the Prius' MAF fuel rates and the injector fuel rates occurred at rates under 2 mL/s. Differences between the two fuel rate estimates generally occurred during transient operation (either increasing or decreasing internal combustion engine load), and for many of the transients, the injector-derived fuel rates appeared to lag the MAF-derived fuel rates by approximately one second. Also, many of the differences between MAF-derived fuel rates and injector fuel rates occurred at transitions between the gas and electric propulsion (i.e., either the internal combustion engine was starting or stopping). This does not appear to be associated with time misalignment or any apparent error in the OBD MAF or injector-derived fuel rates. Instead, this primarily appears to result from comparing two different and rapidly-changing signals with different rise and fall rates over quickly-fluctuating transients. In addition, the relative magnitude (percentage) of these errors is generally high because most of these transients occur at very low fuel rates. As an illustration, consider the data extract in Table 5-14 and shown graphically in Figure 5-16 (this data is from seconds 700 through 707 of the 2011 Prius used for this analysis).

Table 5-14. MAF vs. Fuel Injector Fuel Rate Data during a Startup Transient

Time (s)	RPM (rpm)	MAF (g/s)	Lambda	MAF Fuel Rate (mL/s)	Injector Fuel Rate (mL/s)	|Diff| (mL/s)	% Diff
700	0	0.17	1.03578	0	0	0	0
701	892	0.62	1.165344	0.0507	0.6334	0.582699	1149%
702	1130	7.65	0.910974	0.8003	0.7411	0.059173	7%
703	676	0.96	0.971059	0.0942	0.4056	0.311388	331%
704	0	2.26	1.134173	0.1899	0	0.189894	Inf
705	0	0.5	1.1093155	0.0430	0	0.042953	Inf
706	0	0.2	1.0799745	0.0176	0	0.017648	Inf
707	0	0.18	1.061644	0	0	0	0

Figure 5-16. MAF vs. Fuel Injector Fuel Rate Graph during a Startup Transient



As shown in Figure 5-16, during this brief engine start-up, the two signals achieve approximately the same maximum value (0.8003 mL/s and 0.7411 mL/s at second #702). However, the rate at which these signals rise to their maximum value varies, leading to differences in their values along the way. As described earlier, the injector fuel rate is reported by the OBD system as the volume (mL) of cylinder one's last 10 injections, and this value is then converted to a second-by-second basis (as previously described). This may explain the slower rise and fall of the injector's fuel rate compared to the "quicker" signal from the Prius' hot-wire anemometer mass air flow sensor. As can be seen in Table 5-14, none of the reported values appear unreasonable, they just exhibit different rise and fall rates which is evidenced during transients. This is why the instantaneous values listed in Table 5-14 can vary so significantly, yet the overall average fuel economy averages listed in Table 5-13 are within approximately 3% to 4% of each other.

A summary of the differences in MAF-based vs. injector-based fuel rates is provided in Table 5-15. These values were calculated using the absolute value differences between each of the 1 Hz individual data points in the dataset. As described for the Toyota Camry comparison, the cumulative difference between injector and MAF-based fuel rates is much lower (under 4%) than the average instantaneous difference (approximately 22%) since the average instantaneous difference is calculated with each data point weighted equally (for this test, the difference of the sums differs from the average of the differences).

As shown in Table 5-15, for the entire test, the average of the differences between the MAF fuel rates (with wide-band oxygen sensor adjustments) and the injector fuel rates was 0.065 mL/s, the standard deviation of the differences in fuel rates was 0.1033 mL/s, and the maximum difference seen between the two values was 0.6837 mL/s. The average of the percent differences between the MAF fuel rates and the injector fuel rates was 22%, and the maximum percent difference seen between the two was 1149%. Nine observations had a difference between injector fuel rate and MAF fuel rate greater than 200%. Six of these nine occurred at engine on/off transitions, and all of them occurred at low MAF (and fuel) flow rates (under 1 mL/s). As explained earlier, because of these low fuel flow rates, the absolute difference in fuel flow estimates between the MAF and injector fuel rate estimates was relatively low for these nine observations, between 0.1061 mL/s and 0.5963 mL/s.

Table 5-15. Summary of Differences in MAF-Based and Injector-Based Fuel Rates for 2011 Toyota Prius

Parameter	Fuel Rate |MAF| – FI	Relative |MAF-FI|/MAF	Fuel Rate |MAF – FI|	Relative |MAF-FI|/MAF
	With λ Adjustment		Without λ Adjustment	
Average of the differences between 1 Hz MAF-based and injector-based fuel rates	0.0646 mL/s	22 %	0.0742 mL/s	21 %
Standard Deviation of the differences between 1 Hz MAF-based and injector-based fuel rates	0.1033 mL/s	67 %	0.0963 mL/s	60 %
Maximum difference between 1 Hz MAF-based and injector-based fuel rates	0.6837 mL/s	1149 %	0.7098 mL/s	972 %
Minimum difference between 1 Hz MAF-based and injector-based fuel rates	0.000 mL/s	0.0 %	0.000 mL/s	0 %

5.5.3 Validation using Dynamometer

ERG's subcontractor SGS ETC performed in-laboratory on-chassis dynamometer testing of a 2009 Saturn Outlook using several different test cycles. These tests were conducted at the SGS ETC laboratory in Aurora, Colorado, and the cycles used were the EPA standard city cycle (FTP75), the EPA standard highway fuel economy cycle (HFET), and the aggressive drive cycle (US06). Fuel consumption and emissions were measured on a second-by-second basis during each test, and standard protocols were used to determine the second-by-second fuel consumption and emissions over each drive cycle. Standard SAE J1979 OBDII data was also logged throughout the testing using the HEM Data DAWN Mini datalogger. The analysis, which is described below, compares fuel rate calculated from dynamometer data with fuel rate calculated from OBD data. The analysis compares the fuel rates during normal operation (closed loop and non-enrichment) and also in heavy-throttle/load operation (with enrichment).

The 2009 Saturn Outlook was equipped with a 3.6L V6 gasoline direct injection (GDI) engine. The vehicle was equipped with a mass air flow sensor (rather than using MAP / speed-density) and a narrow-band oxygen sensor. The fuel used was EPA Tier II certification fuel with no ethanol. The specific gravity was 0.7389, and the API Gravity was 60.0.

During all vehicle operation on the dynamometer, the HEM Data logger was installed on the Saturn's OBD port. The dynamometer testing produced two datasets. One set was obtained from the HEM Data logger and included data from standard PIDs. The other set was obtained from the dynamometer test cell and included measurements from the dynamometer and from the constant volume sampling system.

The 2009 Saturn Outlook was tested on a chassis dynamometer over three cycles: the HFET, US06, and FTP75 driving schedules. The FTP75 test was made up the traditional three bags: a cold start for Bag 1, which was immediately followed by Bag 2, then a 600-second soak, which was followed by Bag 3. Two HFETs and two US06s were run with the first of each pair being used to warm up the vehicle for the dynamometer data acquisition on the second of each pair.

For the first test (the FTP75), the test was initiated as a cold start, but only about 15 seconds of cold-start data are available and the vehicle transitioned into closed loop before the initial idle period was over, so an evaluation of OBDII fuel economy estimates during loaded transient open loop operation is not possible with this data.

The analysis described below uses neural network modeling. As will be shown, neural network modeling is used in this analysis to account for time delays and diffusion in the dynamometer data with respect to the OBD data. Without such accounting, direct comparison of dynamometer data with OBD data would lead to the conclusion that their fuel rates do not agree, which is an incorrect conclusion. In this analysis neural network modeling is also used to rapidly screen the influence of potential independent variables, including their curvatures, interactions, and time delays, on variables of interest to fuel economy – in this case, fuel rate. In general, if the neural network cannot find a good relationship among a set of variables, a better traditional ordinary least squares regression model will likely be very difficult to find. However, if a neural network model can predict fuel rate well, then a standard regression model, with its valuable regression statistics, can probably be built. Thus, we do not advocate using a neural network model to be used to predict fuel rates in the main study.

The analysis to determine the ability of standard OBD information to accurately quantify second-by-second fuel economy was carried out using Rockwell Automation's PlantPAx ModelBuilder software. The first step in the analysis was to time-align the HEM Data and dynamometer datasets. This was done by aligning the vehicle speed from the OBD data stream with the vehicle speed from the dynamometer data stream. After alignment, those two speeds had an r^2 of 0.9998 with each other for the data from all three test cycles combined.

Because of the excellent agreement between the vehicle speeds from OBD and from the dynamometer, instead of comparing fuel economies this analysis compares the volumetric fuel flow rate (mL/s) inferred from the OBD data with the volumetric fuel flow rate (mL/s) calculated from the dynamometer data. The dynamometer data contains a variable for the mass fuel flow rate (g/s) based on a carbon balance of the emissions from the vehicle. The volumetric fuel flow rate was calculated from the dynamometer volumetric flow rate using the fuel density according to:

$$\text{DYN\_calc\_FuelRate (mL/s)} = \frac{\text{DYN\_FuelRate (g/s)}}{\text{0.7389 g/mL}}$$

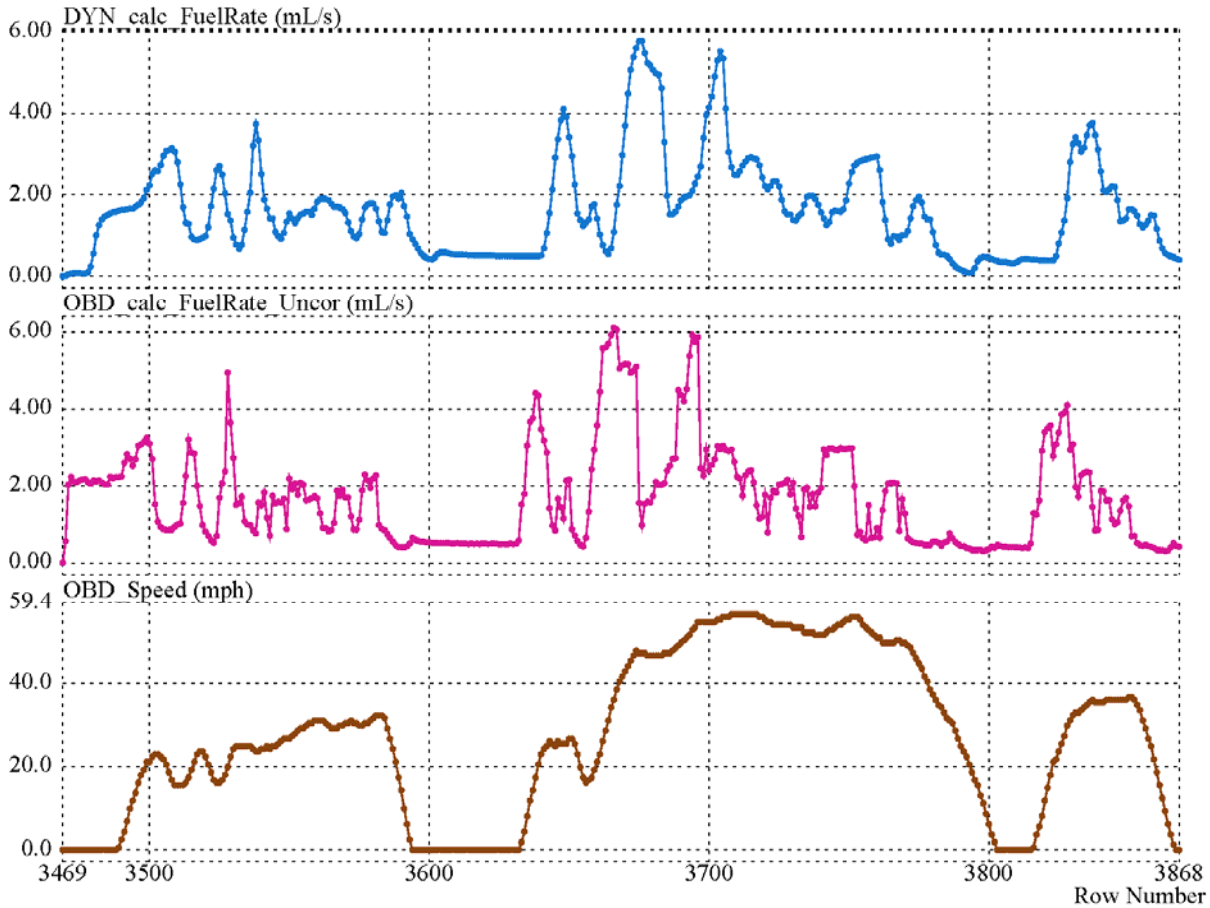
The uncorrected[43] fuel flow, assuming stoichiometric combustion, was calculated from the OBD mass air flow data, the stoichiometric air/fuel ratio for gasoline with 0% ethanol, and the density of the fuel using:

$$\text{OBD\_calc\_FuelRate\_Uncor (mL/s)} = \frac{\text{OBD\_MassAirFlow (g/s) * (1g fuel/14.65 g air)}}{\text{0.7389 g/mL}}$$

Figure 5-17 shows time series plots based on those calculations for the dynamometer fuel flow and the OBD uncorrected fuel flow for the first 400 seconds of the FTP75 Bag 1. The figure also shows the speed of the vehicle as measured by OBD. Each data point on the figure is a one-second measurement.

[43] "uncorrected" means that the calculated volumetric fuel rate has not been corrected for any deviations of combustion from stoichiometric. Later in the analysis, corrections for non-stoichiometric combustion events will be explicitly brought into the calculations.

Figure 5-17. Fuel Flow Rate and Speed Traces During FTP75 Bag1



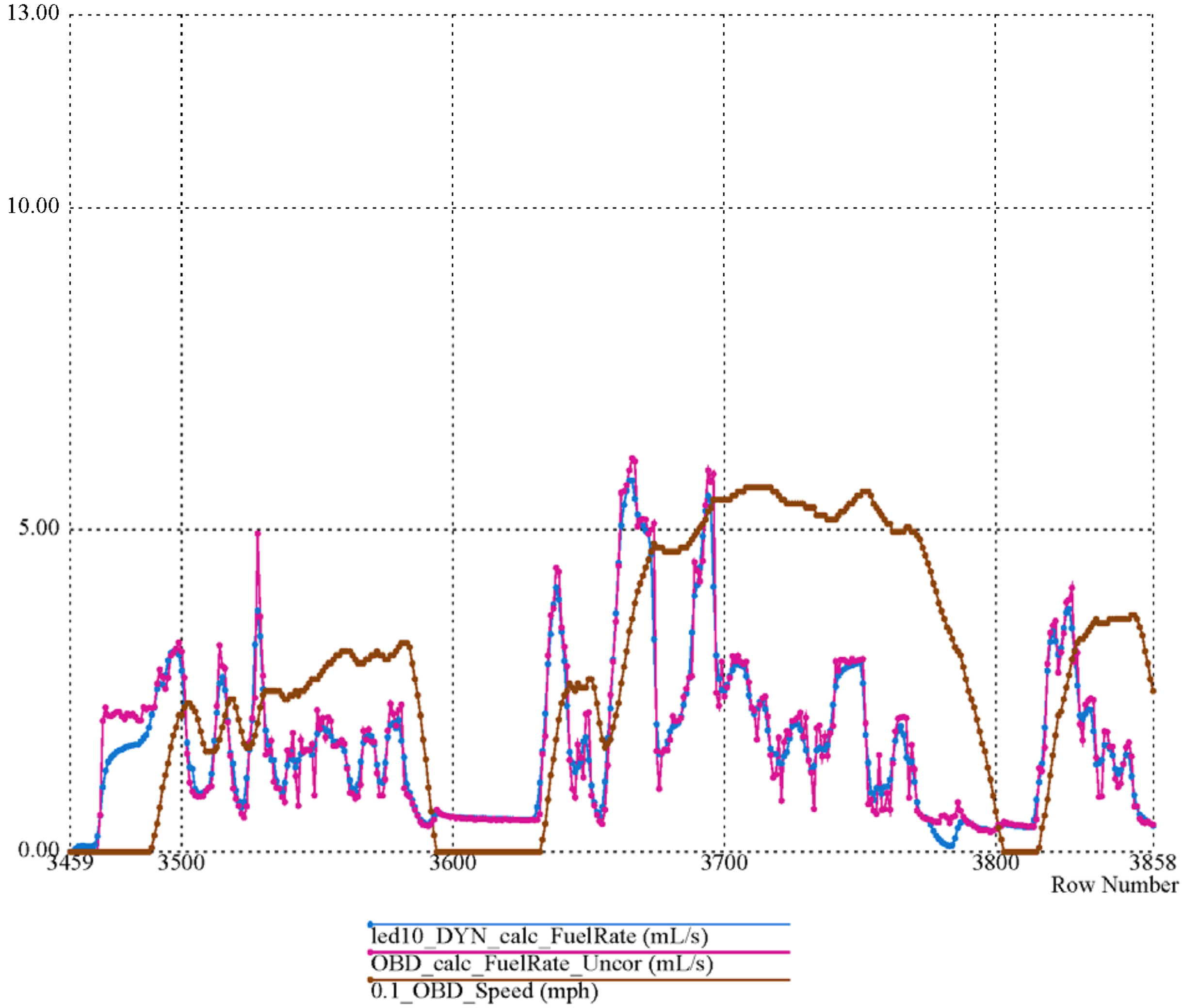
A comparison of the dynamometer fuel flow with the OBD fuel flow shows that two major features are evident from Figure 5-17. First, the dynamometer fuel rate time series is about 10 seconds behind the OBD fuel rate time series. The time required for exhaust gas to move through the vehicle's exhaust system and the constant volume sampling system to finally be measured by the analyzers contributes to this time delay. Another contribution is the time for dynamometer calculations and storage of the results. Second, the OBD fuel rate time series has considerably more high frequency content than the dynamometer fuel rate time series. The dynamometer fuel rate time series appears to be smoothed in comparison with the OBD fuel rate time series. This can be a consequence of the diffusion of CO and CO_2, whose concentrations are used to calculate dynamometer fuel rate, in the exhaust system and constant volume sampling system. Apparent smoothing is also produced by the rise-time and fall-time characteristics of the CO_2 and CO analyzers used to measure concentrations.

The difference in high frequency content of the dynamometer and OBD fuel rate time series is more clearly seen by the overlay plot in Figure 5-18 in which the dynamometer fuel rate time series has been shifted ten seconds[44] earlier. From Figure 5-18, it is evident that a data analysis that compares the observed dynamometer fuel rate with the OBD inferred fuel rate would not produce an excellent agreement because of the difference in the high frequency content of the two time series. However, if one or the other time series could be modified so that both would have the same high frequency content, then a much better agreement for the two measures of fuel flow would result. This, in turn, would produce a more accurate indication of the ability of OBD information to quantify or reflect the actual fuel flow in the engine.

The approach that we chose was to smooth the inferred OBD fuel rate, which has the high frequency content, to produce the dynamometer fuel rate, which has the smoother appearance. The smoothing was accomplished by modeling the dynamometer fuel rate time series as a function of different time delays of the OBD fuel rate time series. This simulates the diffusion and time delay processes that occur during exhaust sampling, dilution, measurement, calculation, and results storage. We used PlantPAx ModelBuilder software to build a neural network model using the combined time series data for the HFET, US06, and FTP75 tests. The input variables were the OBD_calc_FuelRate_Uncor (mL/s) for -6, -7, -8, -9, -10, -11, -12, -13, and -14 second time delays. The output variable was the time series for DYN_calc_FuelRate (mL/s). All 3205 one-second observations of the HFET, US06, and FTP75 were used to train, test, and validate the neural network model. The neural network Model 9 had an r^2 of 0.990, and the standard deviation of the residuals for the fitted dynamometer fuel rate was 0.143 mL/s.

[44] In some plots in this section of this report, some time series are shifted with respect to the raw dataset so that related features on different time series are more clearly revealed. Plotted variable names that begin with "led10_" mean that the data for the variable has been shifted 10 seconds earlier, and "lag10_" means that the data has been shifted 10 seconds later.

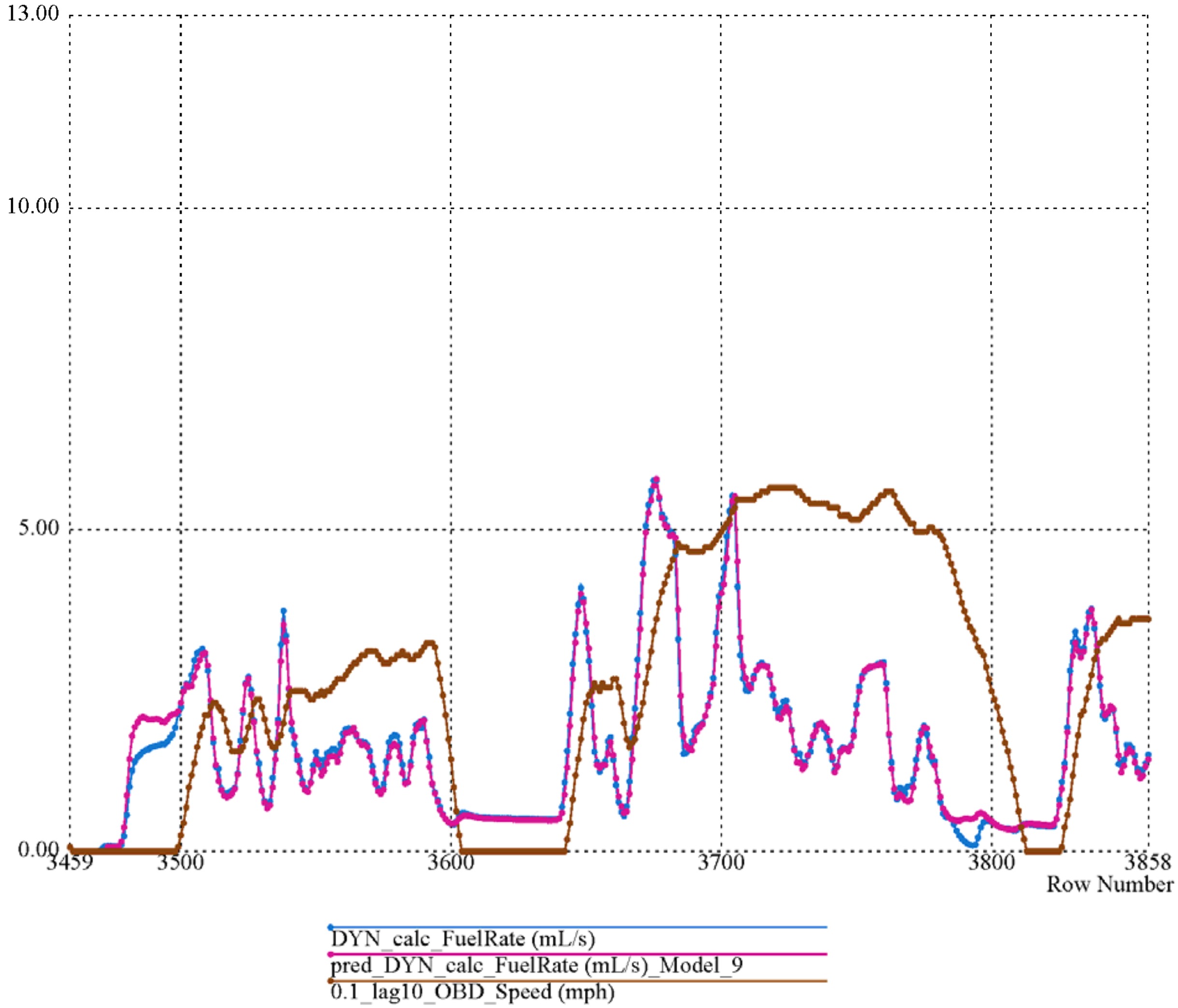
Figure 5-18. Superimposed OBD Inferred and Dynamometer Calculated Fuel Flow Rate During FTP75 Bag1



The fitted values from the model were appended to the original dataset. Figure 5-19 shows a plot of the observed dynamometer fuel rate in blue and the neural network Model 9 prediction values in red for the first 400 seconds of Bag 1 of the FTP. An examination of the plot shows good agreement between the neural network model and the observed dynamometer fuel rates during most of the bag. Two areas where the model did not predict the observed fuel rate well are during the cold start from Row 3480 to 3500 and during the period from Row 3785 to 3800. The speed trace[45] is also shown in Figure 5-19 as the brown line. This shows that the disagreement just before Row 3800 occurs during a rapid and long duration deceleration.

[45] Note that the speed trace is for speed/10 in miles per hour, as indicated by the variable prefix "0.1_".

Figure 5-19. Performance of Model 9 During FTP75 Bag1



We examined the entire time series for the dynamometer test to see if there were other occurrences of a disagreement between the dynamometer fuel rate and the Model 9 fuel rate such as the event just before Row 3800. We found two occurrences in each of the three test cycles for a total of six occurrences[46] that had almost exactly the same characteristics.

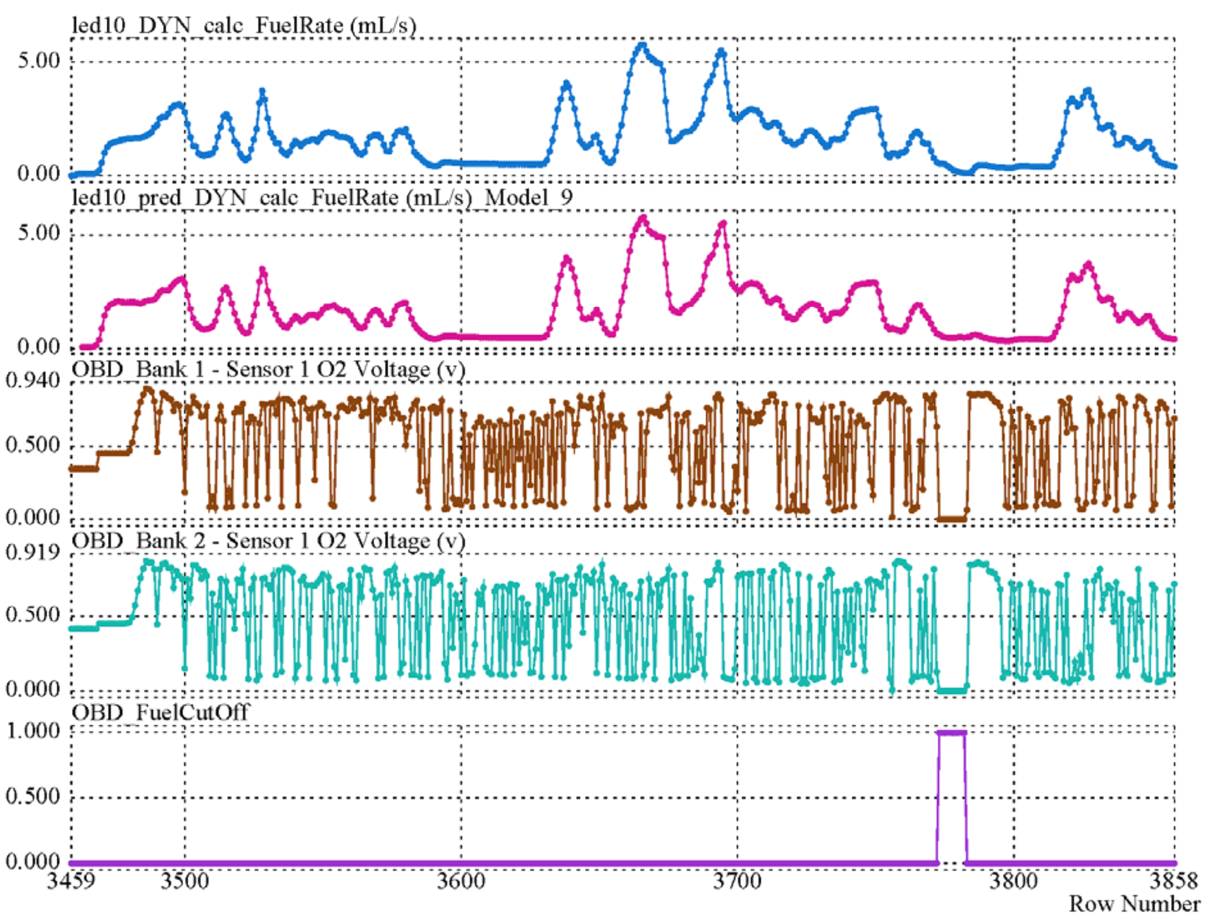
The modeled fuel rate was approximately 0.5 mL/s at each of these six discrepancies, which is approximately the same fuel flow rate measured on many occasions throughout the dataset during engine idling and moderate vehicle decelerations. On the other hand, the dynamometer-measured fuel rate was about 0.1 mL/s at the bottom of the dip at each of the six discrepancies. We suspected that the dips in the observed dynamometer fuel rate, such as the blue dip in Figure 5-19 just before Row 3800, may represent the effects of fuel cut-off by the

[46] At these rows on an unshifted time scale for DYN_calc_FuelRate: 1075, 1534, 2634, 3015, 3793, and 5779.

engine management system. We postulated that if fuel cut-off were actually occurring, its effect might be recorded in the OBD data stream.

Figure 5-20shows the first 400 seconds of Bag 1 of the FTP75 cycle with the DYN and predicted DYN fuel rates shifted 10 seconds early to align with OBD variables. The traces show that the OBD Bank 1 O2 Sensor voltage and OBD Bank 2 O2 Sensor voltage dropped to 0.000 volts just before the point of disagreement between observed and predicted dynamometer fuel rate. The histograms of the OBD Bank 1 and Bank 2 O2 Sensor voltages, which are shown in Figure 5-21, are dominated by two modes with one centered at about 0.1 volts and another centered at about 0.7 volts for the narrow band oxygen sensors that are used for this engine. In addition, the histograms for the Bank 1 and Bank 2 sensors show a small peak of about 127 seconds of operation where the voltage is recorded as exactly 0.000 volts. It is during these seconds that we postulated that fuel cut-off to the engine was occurring.

Figure 5-20. Searching for Fuel Cut-Off Indicators



To test this hypothesis, we created an indicator variable for fuel cut-off, OBD_FuelCutOff. If the OBD Bank 1 O2 Sensor and OBD Bank 2 O2 Sensor were both between 0.000 and 0.001 volts, OBD_FuelCutOff was assigned a value of 1; else OBD_FuelCutOff was assigned a value of 0 at all other times. Then, we built another neural network called Model 10 that was the same as Model 9, except that in addition to time delays inputs for OBD uncorrected fuel rate, Model 10 had inputs for OBD_FuelCutOff at time delays of -8, -9, -10, -11, -12, -13, -14, -15, and -16 seconds. The r^2 of this regression was 0.992 with a standard deviation of the residuals of 0.124 mL/s. The various time delays for the OBD_FuelCutOff variable allow the effects of diffusion on a fuel cut-off at the engine to be modeled as seen in the dynamometer fuel flow time series.

Figure 5-21. Histograms of OBD Bank1 and Bank 2 Oxygen Sensor Voltages

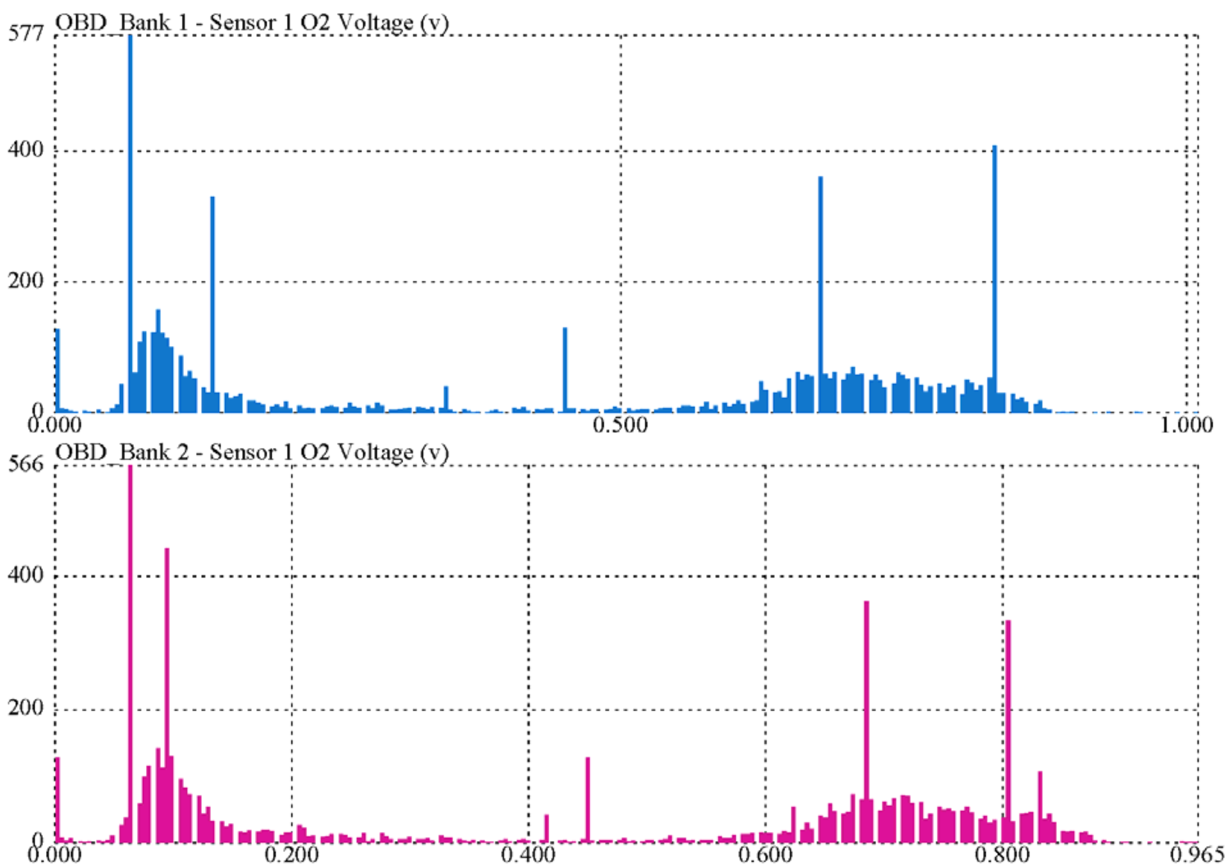
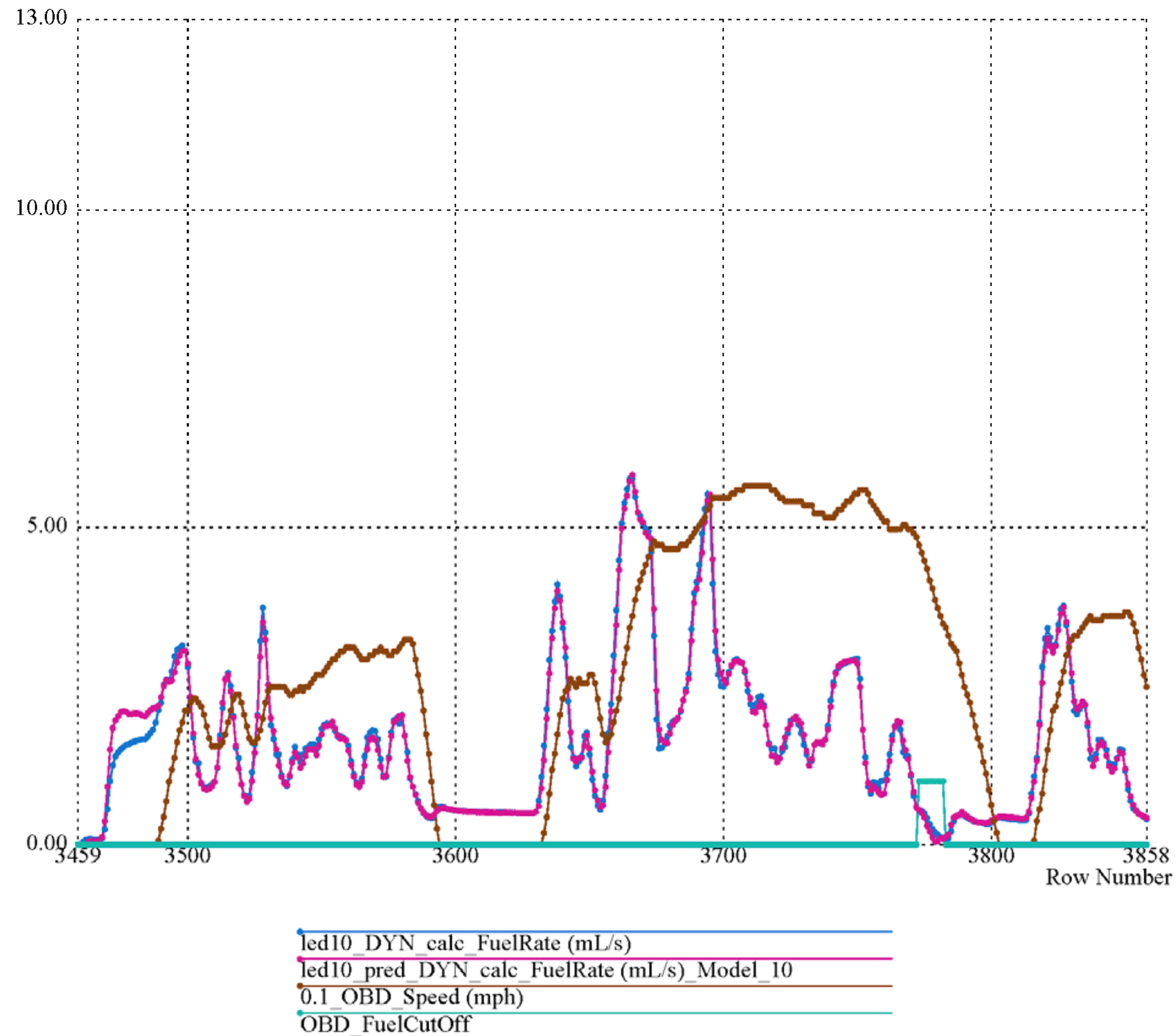


Figure 5-22 shows the improvements by Model 10 for Bag 1 of the FTP75 test. The plot shows the observed dynamometer fuel rate in blue, the predicted results from Model 10, which includes the effects of fuel cut-off, in red, the OBD_FuelCutOff indicator variable in turquoise, and the speed/10 trace in brown. The plot shows that the inclusion of the OBD_FuelCutOff variable in Model 10 greatly improves the fit of the data just before Row 3800. The other five occurrences of disagreements between the observed dynamometer fuel rate and the fuel rate predicted by Model 9 showed no substantial disagreement with Model 10. At the same time, the Model 10's ability to predict fuel flow in regions where presumed fuel cut-off was not occurring was just as good as for Model 9.

Figure 5-22. Performance of Model 10 During FTP75 Bag1



At this point, the sole remaining discrepancy between the modeled and observed dynamometer fuel flow rate occurs during the first 20 seconds of Bag 1 of the FTP. These 20 seconds are the only observations in the entire dynamometer dataset where the engine was started after an overnight soak and where the actual fuel rate was measured by the dynamometer. We examined the time series of OBD variables for the entire dataset to find variables that had specific and distinct values during the 20 second cold start and did not have those values at any other time in the dataset, with the possible exception of a few single spurious values here and there. We found that the OBD_CommandedEquivalenceRatio, a standard OBD PID, met this requirement. OBD_CommandedEquivalenceRatio values greater than 1 indicated lean operation, values less than 1 indicate rich operation, and values equal to 1 indicate stoichiometric operation.

During the 20 seconds of cold start data in Figure 5-22 (Rows 3470 to 3490) the dyne-measured fuel rate (blue) is lower than the fuel rate predicted by Model 10 (red). The Model-10-predicted fuel rate values at non-fuel-cut-off conditions are on a stoichiometric basis since the majority of the data used to build the model is stoichiometric data. Thus, these values indicate that engine operation is actually lean during this cold start since the measured fuel rate (blue) is lower than the values expected for stoichiometric operation (red). An estimate of the lambda during the cold start is the ratio of the red to the blue values – about 1.3. Thus, the data indicates that, during this cold start, engine management seems to be commanding enleanment rather than enrichment. This could be the result of the use of fast idle controls and spark retard by this modern vehicle to warm the catalyst up quickly and to minimize emissions after cold starts.

Despite the reason for the engine management strategy on this vehicle, the data indicates a lean condition during cold starts. In addition, during the 20 seconds of that cold start the OBD_CommandedEquivalenceRatio had values between 1.024 and 1.029, as shown in Figure 5-23 for Rows 3470 to 3490. After such a cold start, the oxygen sensor is cold and is not functioning. Therefore, the manufacturer may be feeding some sort of default value to the OBD_CommandedEquivalenceRatio PID. In contrast, during Bag 3 of the FTP75, which has the same speed trace but during which the engine undergoes a hot start, the OBD_CommandedEquivalenceRatio is 0.999, as shown in Figure 5-24 for Rows 5455 through 5475. The other time when the OBD_CommandedEquivalenceRatio observations fell in the 1.024-to-1.029 range, was during the first 14 consecutive seconds of the first HFET drive. Because this drive was used to warm up the vehicle for the second and tested HFET, no dynamometer results are available. In the entire dataset, only two other isolated one-second observations of OBD_CommandedEquivalenceRatio in this cold start range (1.024 to 1.029) were scattered throughout the dataset.

As mentioned earlier, the measured fuel rate and estimated stoichiometric fuel rate during the cold start (Rows 3470 to 3490) indicated a lambda of about 1.3. On the other hand, during this same period the OBD_CommandedEquivalenceRatio had reported values between 1.024 and 1.029. While both sets of values indicate that engine operation is lean during the cold start, the values disagree in the degree of leanness that the sets of values imply. This discrepancy suggests that the values of OBD_CommandedEquivalenceRatio for this engine under this single cold start appeared to be only a qualitative indicator of stoichiometry. Accordingly, using values of OBD_CommandedEquivalenceRatio to directly calculate fuel rate during non-stoichiometric operation may be inappropriate. However, OBD_CommandedEquivalenceRatio may be able to indicate when fuel cut-off or cold starts may be occurring.

To try to evaluate this possibility, we created an indicator variable for cold start fuel management to be used for modeling, OBD_ColdStart. If the OBD_CommandedEquivalenceRatio is between 1.024 and 1.029, OBD_ColdStart was assigned a value of 1; else it was assigned a value of 0.

Figure 5-23. Searching for Fuel Enrichment Indicators During FTP75 Bag1

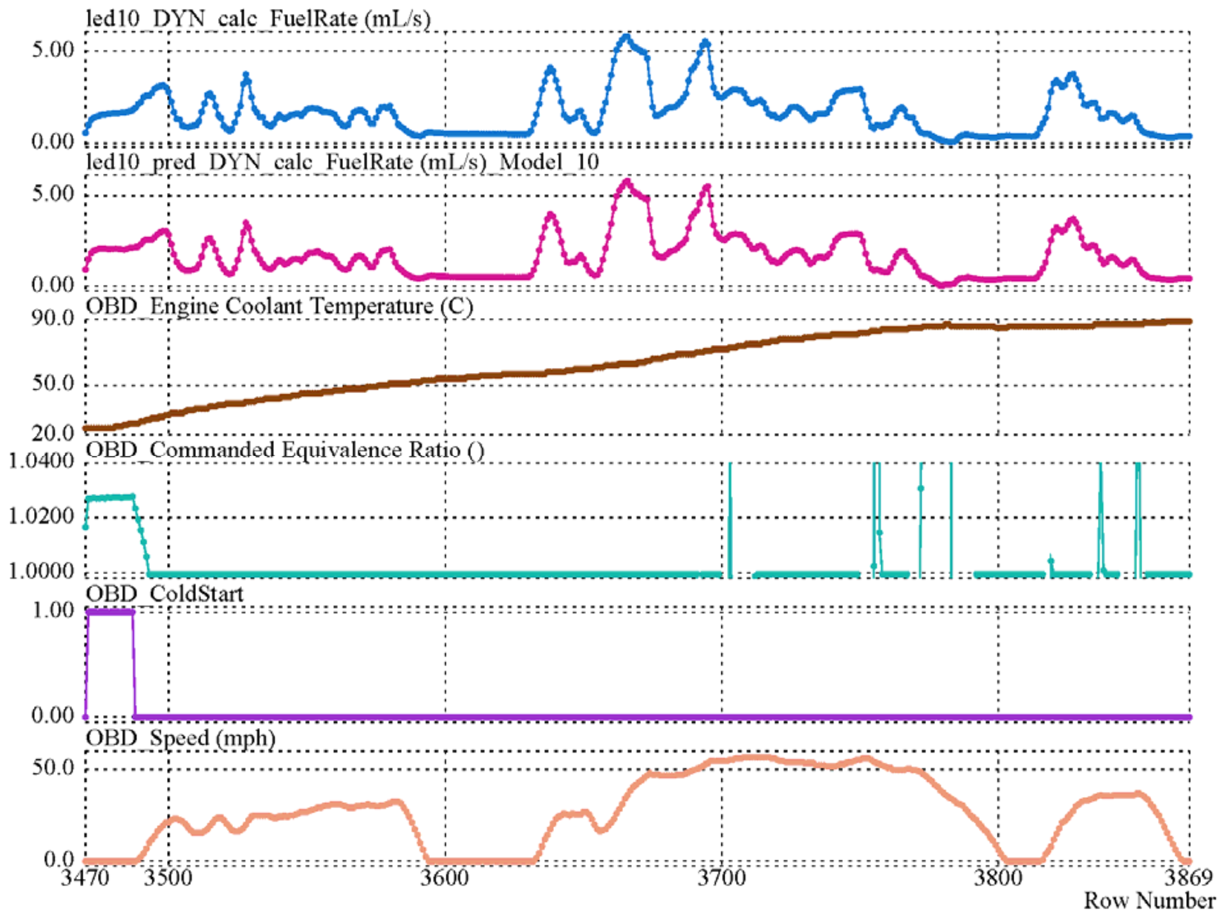
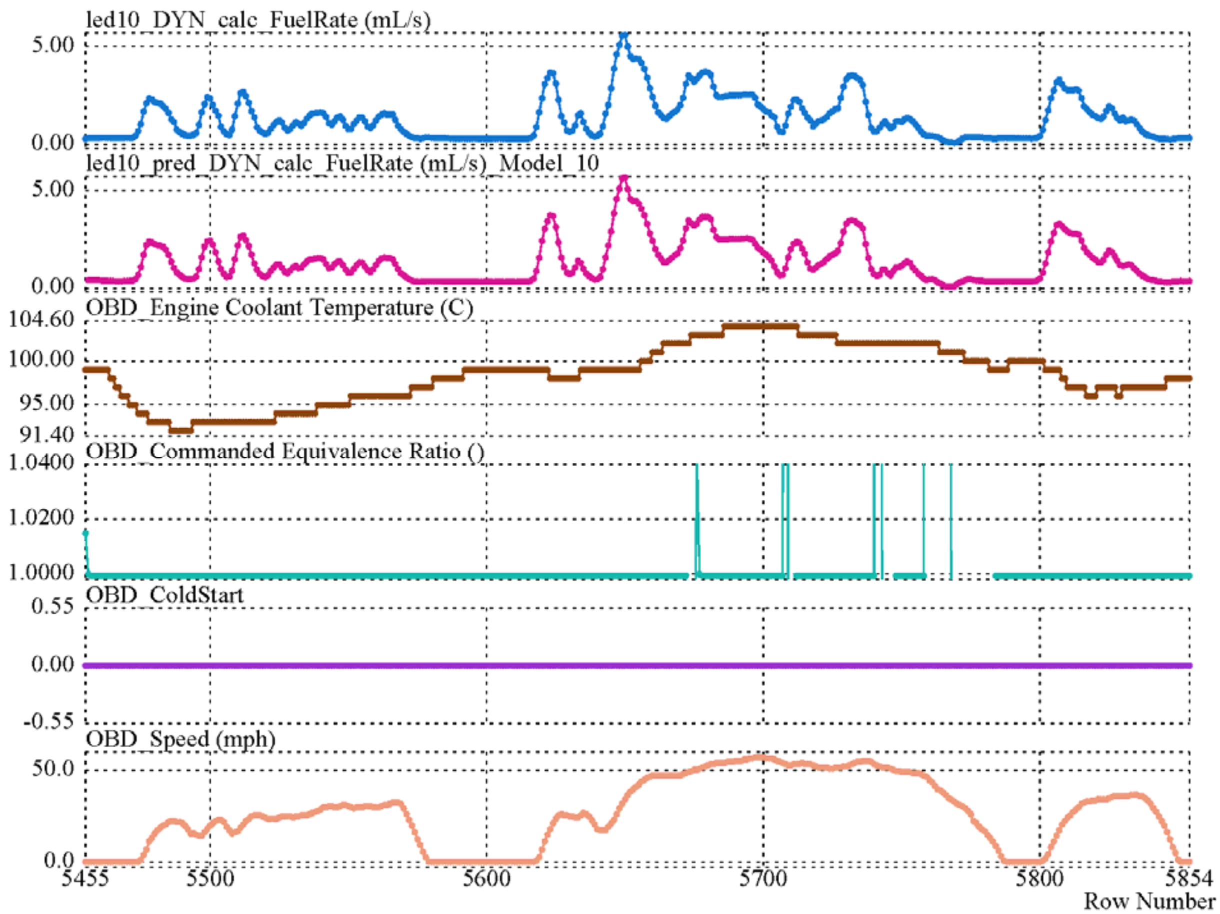


Figure 5-24. Searching for Fuel Enrichment Indicators During FTP75 Bag3



Based on these observations of certain values for OBD_CommandedEquivalenceRatio during the cold start of Bag 1 of the FTP75 and the cool start of the warm-up HFET drive, a third neural network Model 11 was built to incorporate the effects of non-stoichiometric combustion during some engine-starting events. Model 11 had inputs of OBD_calc_FuelRate_Uncor (mL/s) with time delays of -6 to -14 seconds, the indicator variable OBD_FuelCutOff with time delays of -8 to -16 seconds, and the indicator variable OBD_ColdStart with time delays of -8 to -16 seconds. The response variable that was modeled was DYN_calc_FuelRate (mL/s). The model had an r^2 of 0.993 and the residuals of the predicted dynamometer fuel rate had a standard deviation of 0.117 mL/s as is shown in Figure 5-25.

Figure 5-25. Parity Plot for Model 11 for All Three Test Cycles

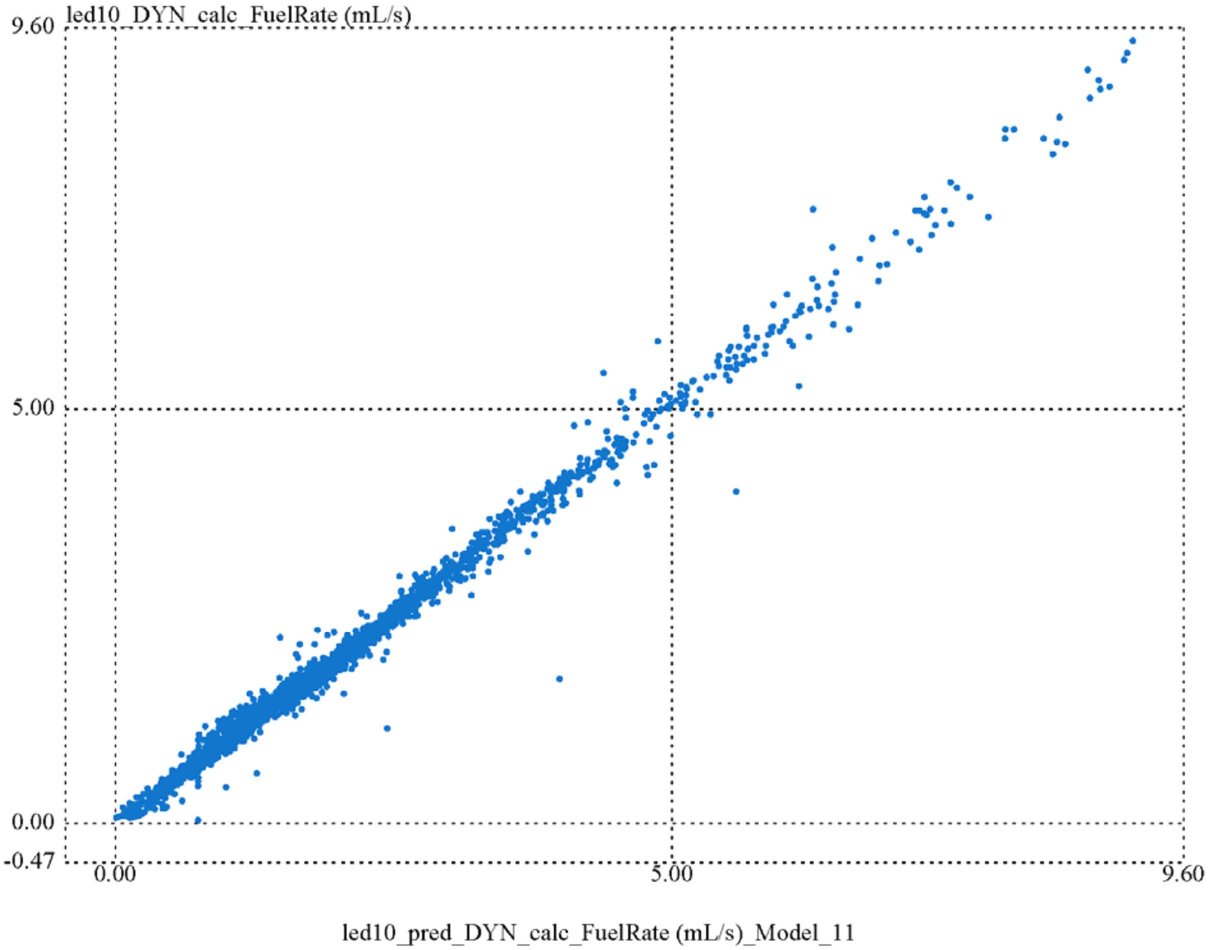
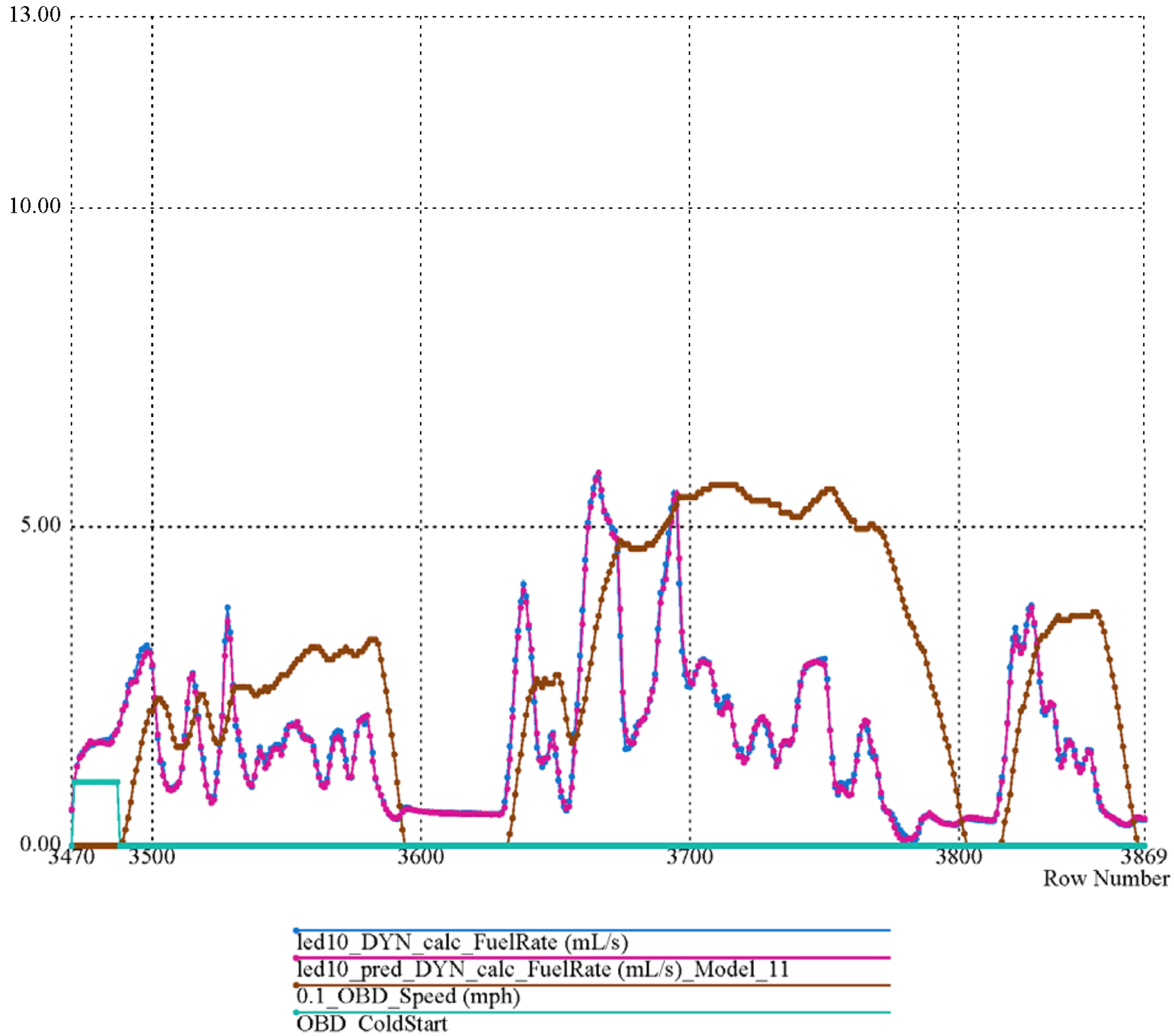


Figure 5-26 gives an indication of the performance of Model 11 for the first 400 seconds of Bag 1 of the FTP75. Concentrating on Rows 3470 through 3490, the figure shows that the predicted values by Model 11, in red, are largely coincident with the observed dynamometer fuel rate, in blue, and are a major improvement over the previous Model 10 predicted values shown in Figure 5-22 in Rows 3470 through 3490. The turquoise OBD_ColdStart variable trace, which is based on the OBD_CommandedEquivalenceRatio, indicates that combustion was non-stoichiometric – specifically, combustion was modified by engine controls for a cold start – during the first 20 seconds of Bag 1 of the FTP75.

Figure 5-26. Performance of Model 11 During FTP75 Bag1



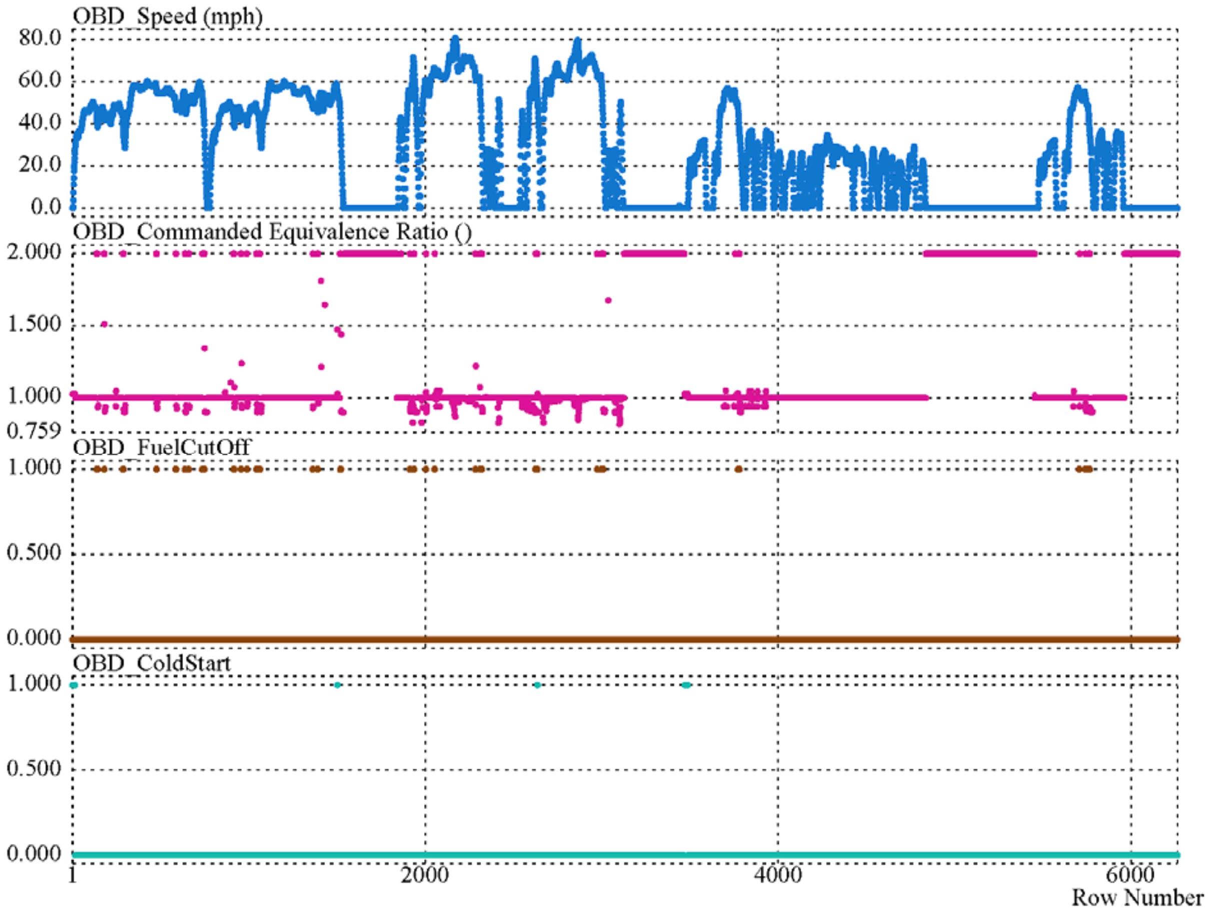
An examination of the observed and Model 11 predicted dynamometer fuel rate values for the entire dataset shows that Model 11 fits the observed fuel flow values under all conditions tested, including during the cold start and the six fuel cut-off events. The entire time trace for all three test cycles is shown in Appendix B. The observed dynamometer fuel rate is shown in blue. The dynamometer fuel rate predicted by Model 11 is shown in red. The OBD_FuelCutOff indicator variable is shown in brown. The OBD_ColdStart indicator variable, which is called OBD_Enrichment in the appendix, is shown in turquoise. The OBD speed/10 is shown in purple.

Subsequent to the development of Model 11, we saw that the OBD_CommandedEquivalenceRatio could also be used to determine fuel cut-off events, as well as the cold start. Figure 5-27 shows a comparison of the OBD_CommandedEquivalenceRatio with the OBD_FuelCutOff indicator variable, which was determined from the Bank 1 and 2 O2

Sensor voltages, and the OBD_ColdStart variable, which was determined from the OBD_CommandedEquivalenceRatio variable for the entire dataset. The figure's top trace, which is for speed, shows that the dataset is made up of two HFETs, two US06s, and one FTP75. The plot shows that for all events when OBD_CommandedEquivalenceRatio is near 2, the OBD_FuelCutOff equals 1. In addition, OBD_CommandedEquivalenceRatio values near 2 occur when the engine is turned off between test cycles. Detailed examination of the data indicates that with regard to fuel cut-off, OBD_CommandedEquivalenceRatio contains the same information.

Figure 5-27 also shows that the dataset contained numerous instances where the OBD_CommandedEquivalenceRatio was less than 1 (indicating commanded rich operation). Since the agreement between the dyne-measured fuel rate and the fuel rate predicted by Model 11 was excellent throughout the dataset, these rich values of OBD_CommandedEquivalenceRatio were not needed in the model. Nevertheless, a model was built to determine if using the values of OBD_CommandedEquivalenceRatio would improve the model. The resulting model was not an improvement over Model 11.

Figure 5-27. Examining OBD_CommandedEquivalenceRatio as an Indicator of Fuel Cut-Off



Overall, the analysis so far indicates that the observed dynamometer fuel rate is closely related to just two variables: the OBD mass air flow and the OBD commanded equivalence ratio. The OBD mass air flow is used to calculate the fuel flow rate, assuming stoichiometric combustion. This works for most, but not all, operating conditions. The analysis indicates OBD commanded equivalence ratio can be used to identify periods of fuel cut-off and non-stoichiometric operation. These findings lead to an overall proposed algorithm that can be used to estimate the fuel flow at the engine based solely on standard (non-enhanced) OBD parameters. The algorithm is made up of three factors: 1) calculation of the fuel rate assuming stoichiometric combustion, 2) a factor that turns off the fuel during fuel cut-off, and 3) a factor that modifies the fuel rate during non-stoichiometric operation[47]:

[47] At cold temperatures or under extended high-load situations, which were not used to generate this dataset, the fuel injection system may behave completely differently. Under other types of conditions, the mechanism for non-stoichiometric operation may be completely different from the cold start behavior seen in the dataset.

$$\text{OBD\_FuelRate (mL/s)} = \frac{\text{OBD\_MassAirFlow (g/s)} * \text{(1g fuel/14.65 g air)}}{\text{0.7389 g/mL}}$$

$$* \text{ if (OBD\_FuelCutOff} = 1, 0, 1)$$

$$* \text{ if (OBD\_ColdStart} = 1, 0.77, 1)$$

where

$$\text{OBD\_FuelCutOff} = \text{if } (1.98 \leq \text{OBD\_CommandedEquivalenceRatio} \leq 2, 1, 0)$$
$$\text{OBD\_ColdStart} = \text{if } (1.024 \leq \text{OBD\_CommandedEquivalenceRatio} \leq 1.029, 1, 0)$$

The argument of 0.77 in the third factor of the algorithm was needed to best-fit the dyne-measured fuel rate during the cold start operation at the beginning of Bag 1 of the FTP75 for the 2009 Saturn Outlook with a GDI engine. This value suggests that the vehicle was running lean during this cold start. During the first 20 seconds of Bag1 of the FTP75, the dynamometer-measured fuel rate is lower than the fuel rate predicted by Model 10 (see Figure 5-22). Model 10 was trained on the full dataset, which is dominated by warmed-up engine operation. Therefore, the predicted fuel rates by Model 10 are those expected by a warmed-up engine. Since the measured fuel rate is lower than that predicted by Model 10, the engine seems to be running leaner than stoichiometric. Also, if OBD_CommandedEquivalenceRatio equals 1.000 at stoichiometric and OBD_CommandedEquivalenceRatio equals 1.999 for fuel cut-off and engine-off, which are both very lean, then an OBD_CommandedEquivalenceRatio of 1.024 to 1.029 would be on the lean side of stoichiometric. Modern vehicles have fast idle controls, combined with spark retard, to warm the catalyst up quickly after cold starts. It is possible that these fast idle controls bypass the MAF sensor.

Development of the neural network models do not prove that the fuel flows that are measured by the dynamometer agree with fuel flows inferred from the OBD data. The neural network models merely identify which OBD variables are influential and could be used to calculate a fuel flow based on OBD parameters. To verify or determine the accuracy of the proposed algorithm given above, the fuel flows calculated by the algorithm and measured from the dynamometer data need to be compared. The problem with doing this comparison on a second-by-second basis is, as mentioned in the beginning of this discussion, that the OBD data contains high frequency information that is not present in the dynamometer data because of the diffusion and time delay processes that influence the fuel flow values calculated from the dynamometer measurements. One way to get around this difference in high frequency content is to consider the cumulative fuel over a segment of engine operation using second-by-second fuel flows inferred from OBD data and calculated from dynamometer data.

We have performed these calculations separately for the tested HFET, US06, Bag 1, Bag 2, and Bag 3 of the FTP75 cycles of this dataset. Table 5-16 shows the volumes of fuel calculated from these two data sources. The results indicate that the proposed OBD fuel algorithm given above "recovers" 100% of the fuel volume measured by the dynamometer, with an accuracy of about three percent. The agreement has also been verified on a five- to ten-second time scale by examining the cumulative fuel volumes inferred from OBD parameters using the algorithm and measured by the dynamometer within each of the three test cycles.

Table 5-16. Comparison of Total Fuel Inferred from the OBD Algorithm and Calculated from Dynamometer Measurements

Cycle	Duration (s)	Cumulative Fuel Volume (mL)		Recovery (%)
		Dynamometer Calculations	OBD Algorithm	
HFET	765	1392.8	1409.2	101.2%
US06	600	1793.4	1841.3	102.7%
FTP75 Bag1	505	810.0	816.8	100.8%
FTP75 Bag2	863	851.8	858.7	100.8%
FTP75 Bag3	505	667.7	681.9	102.1%

Overall, this analysis of the OBD data and the dynamometer measurements indicates that, at least for this vehicle, the OBD mass airflow and the OBD commanded equivalence ratio are sufficient to produce an accurate estimate of fuel flow rate at moderate ambient temperatures. With that fuel flow estimate and the OBD data stream for vehicle speed, the second-by-second fuel economy can be easily calculated by division. Under stoichiometric combustion conditions, the OBD mass airflow values along with the stoichiometric air fuel ratio and fuel density are all that is required to calculate the fuel flow rate.

For non-stoichiometric and fuel cut-off events of this single vehicle tested on the dynamometer, certain special values of the OBD_CommandedEquivalenceRatio (1.024 to 1.029, and 1.98 to 2.00) were needed to create the OBD_FuelCutOff and the OBD_ColdStart indicator variables. The special OBD_CommandedEquivalenceRatio values that were used to create these two indicator variables could differ from one vehicle to another. In the main study, these special values would not be known *a priori* for each vehicle. However, as long as data collection during the main study includes OBD_CommandedEquivalenceRatio and variables that are related to it, for example, the OBD short term fuel trim percents and voltages, we expect that an analysis conducted on the OBD data for each individual vehicle from the main study could be used to determine the special values that are needed to define fuel cut-off and enrichment events for each individual vehicle. For example, the range of OBD_CommandedEquivalenceRatio for fuel cut-off events would be the same values that would be observed when the engine is off, and the range of values that correspond to cold-start non-stoichiometric operation would be those that are seen during the beginning of engine operation after a 12-hour soak – something that would happen to all instrumented vehicles on most days.

5.6 Future Proposed Analysis

As described in this report, we recommend additional analyses of some key issues prior to moving forward with a larger-scale study, as this analysis would help provide information needed to reduce study costs and enhance data quality. The focus of these activities will be to provide information that can be used to assess the relative benefits and cost-effectiveness of using standard OBD PIDs versus enhanced OBD PIDs in the main study. One advantage of using enhanced OBD PIDs for the main study is that fuel flow rate or surrogates for fuel flow rate may be available when mass air flow (or non-stoichiometric operating information) is not available. However, while using enhanced PIDs to determine fuel flow rate may be feasible, acquiring and interpreting enhanced PID data appears to be a formidable task, and some potential accuracy issues have been identified with calculating fuel rate from enhanced PID data. On the other hand, while standard PIDs are far easier to obtain and interpret, using them to calculate fuel flow rate – especially for vehicles without mass air flow, for operation during non-stoichiometric conditions and for diesel engines – can lead to deviations between the calculated fuel flow rate and the actual fuel flow rate. Thus, quantifying the size of the deviations and their rate of occurrence in the fleet will aid in deciding between using standard and enhanced PIDs.

5.6.1 Evaluate MAP-to-MAF Conversion Calculations

As previously discussed, many vehicles use manifold absolute pressure rather than mass air flow as an input to determine fuel rate, so these vehicles do not broadcast values for the mass air flow standard PID but instead broadcast values for the manifold absolute pressure standard PID. To calculate fuel flow rate for these vehicles, the manifold absolute pressure may be converted to mass air flow. This conversion depends on the engine's volumetric efficiency, which is a function of engine design, RPM, and load. While volumetric efficiency depends on the design of each engine's air intake system, it is likely that for typical consumer vehicle engines (i.e., non-racing engines) the volumetric efficiency surfaces (a function of RPM and load) will lie reasonably close to each other. An average of the surfaces from many vehicles could be used to convert manifold absolute pressure to mass air flow. Although these surfaces will lie reasonably close to each other, an error will be incurred for each engine because the surface for some engines will tend to be above the average surface and others will tend to be below.

This task could be accomplished using 57 vehicles from the Kansas City study dataset that have broadcasted standard OBD PIDs for both mass air flow and manifold absolute pressure to determine the distribution of volumetric efficiency surfaces and the average surface. An analysis of those surfaces would quantify the distribution of uncertainties in calculated mass air flow rate when converting MAP to MAF in the main study.

5.6.2 Calculate Fuel Flow Rate for Mass Air Flow / Narrow-Band Oxygen Sensor Gasoline Vehicles

As previously described, two different types of oxygen sensors are used on vehicles to determine stoichiometry: wide-band oxygen sensors and narrow-band oxygen sensors. For the purposes of calculating fuel flow rate, wide-band oxygen sensors are preferred since they 1) reveal when the engine deviates from stoichiometric and 2) they report the lambda[48] of the combustion mixture during each of those deviations. Accordingly, using the standard PID for lambda is expected to produce accurate values for calculated fuel flow rate. On the other hand, narrow-band oxygen sensors only reveal when the engine deviates from stoichiometric, but they cannot accurately determine how rich or lean the mixture is.

When engines equipped with narrow-band oxygen sensors go into a non-stoichiometric operating condition, the fuel flow rate can be estimated using an average lambda for the type of non-stoichiometric event that is occurring. This would be an improvement over simply using lambda=1 for all events. This task could be accomplished using the 169 Kansas City study vehicles that have narrow-band oxygen sensors and broadcast the standard PID for mass air flow to calculate the effective lambdas for starts, fuel cut-offs, and high loads. The effective lambdas would be calculated as the ratio of the fuel flow rate measured by PEMS to the stoichiometric fuel flow rate modeled using the neural network software so that time delays and diffusion are taken into account. A distribution of effective lambdas would be made up of the individual lambdas obtained from all of the non-stoichiometric events of the same type taken from all of the vehicles in this dataset. If possible, the lambda distributions for starts and high loads could be further split by coolant temperature and load, respectively. The relative deviations of the individual lambdas from the average lambda would translate directly to the deviations between

[48] Lambda is a quantity that quantifies the stoichiometry of the mixture: lambda=1 is stoichiometric, lambda > 1 is lean, and lambda < 1 is rich.

estimated fuel flow rate and actual fuel flow rate. The overall result would be an estimate for the relative error in fuel flow rate for each type of non-stoichiometric event.

5.6.3 Calculate Fuel Flow Rate for Manifold Absolute Pressure / Narrow-Band Oxygen Sensor Gasoline Vehicles

Vehicles that both do not broadcast mass air flow and have narrow-band oxygen sensors have two sources of error: one source from the conversion of MAP to MAF and another from the uncertainty in lambda that arises from the narrow-band oxygen sensor. Theoretically, the errors from the analysis described in Sections 5.6.1 and 5.6.2 should simply add together, but a better approach to estimate this error would be to perform a separate analysis of the 192 Kansas City study vehicles that broadcast manifold absolute pressure. This would be done by converting the manifold absolute pressures using the average volumetric surface determined as described in Section 5.6.1, and then using the oxygen sensor lambda analysis techniques described in Section 5.6.2. Again, the overall result would be an estimate for the relative error in fuel flow rate during stoichiometric and non-stoichiometric operation.

5.6.4 Analyze Light-Duty Diesel Vehicle Exhaust Data and OBD Data

Combustion control for a diesel engine is different than for a gasoline engine. Combustion is always lean and therefore non-stoichiometric. Nevertheless, diesel engine computers determine the amount of fuel to inject based on RPM, load, accelerator position, intake air temperature, and mass air flow or manifold absolute pressure, among other parameters. Therefore it may be possible to calculate fuel flow rate, or at least relative fuel flow rate, based on the quantities that are standard OBD PIDs. To convert relative fuel flow rate to absolute fuel flow rate, the rated power and displacement of each engine may be required.

ICCT has acquired data on two diesel vehicles. The vehicles were operated on an ARB dynamometer to generate OBD data and calculated fuel flow rate from exhaust emissions and flow measurements. The same two vehicles were also operated on the road while collecting OBD data and PEMS-calculated values of fuel flow rate. In addition, ERG has obtained in-use diesel OBD data, which includes OBD fuel flow rate, on a 2011 VW Touareg TDI and a 2012 VW Passat TDI. For this task, ERG would analyze the diesel data on these four vehicles with the goal of determining how well fuel flow rate can be estimated from standard OBD PIDs.

5.6.5 Determine the Standard PIDs that are Populated with Data by Year, Make, Model, Engine and Fuel

While SAE J1979 defines standard PIDs, not all standard PIDs are broadcast on any particular vehicle, and vehicle manufacturers elect which PIDs are broadcast, by vehicle, based on that vehicle's engine management strategy and emissions control equipment. Since these technologies differ among model year, make, model, engine and fuel, the slate of standard PIDs that are populated by different vehicles differ. Although it may be possible to have a "general" PID-request configuration for all dataloggers to be used in the study, knowing which PIDs are broadcast for any specific vehicle prior to beginning a main study could be beneficial in optimizing vehicle-specific datalogger configurations in the main study. This will help ensure the optimal data is collected for each vehicle and minimize the possibility of reduced sampling rates resulting from oversampling (requesting more PIDs than can be collected on a 1-Hz basis). This "tailored" configuration approach would require the contractor know in advance which standard PIDs are broadcast, by vehicle, in order to configure each datalogger prior to installation on each participating vehicle.

For this task, a datalogger would be installed for about 1 minute on 1996-2013 vehicles as they are inspected (and run) at a state inspection/maintenance station. Data would be collected on all standard PIDs that could possibly be used for determination of fuel flow rate and fuel economy. The data collected would indicate which standard PIDs are populated for each combination of model year, make, model, engine, and fuel. An analysis of the data collected in this task would produce a table of standard PIDs broadcast for the most common vehicles in the fleet. In addition, results of this task would also provide information regarding the use of MAF vs. MAP and narrow- vs. wide-band oxygen sensors, by manufacturer, model year, make, model, engine, and fuel type. To minimize costs, the field portion of this task could be performed for two or three months during a school break by a student who resides in the same city as the inspection/maintenance station.

5.6.6 Perform additional evaluation of enhanced PID data

As shown in Section 5.5.2 (Standard SAE J1979 PID vs. OEM-enhanced PID Validation), some issues were identified regarding discrepancies between the fuel injector-based fuel rate (fuel rate based on an enhanced PID) and the MAF-based fuel rate. As mentioned in Section 5.5.2, prior to proceeding with a study in which enhanced PID data is used to determine fuel economy, additional investigation regarding the source of the discrepancy would be warranted. At a minimum, this might entail collecting standard MAF/oxygen sensor data (standard SAE J1979 data), enhanced fuel rate data and either mass-based dynamometer or

PEMS data for one or more vehicles. This would provide an independent measure of fuel rate in order to reveal the source of the discrepancy between the two fuel rate estimates.

5.6.7 Collect and analyze additional OBD / dynamometer data from ongoing laboratory work

In order to supplement the analysis described in Section 5.5.3 (Dynamometer Validation), the feasibility of performing additional OBD / dynamometer data collection could be explored. For example, testing could be conducted at the SGS/ETC laboratory (where the dynamometer / OBD testing was performed on the 2009 Saturn for the analysis in Section 5.5.3). Costs could be minimized by making arrangements with SGS/ETC to collect OBD data on in-house testing already being performed at the laboratory. These arrangements would involve SGS/ETC providing dynamometer/OBD test data to ERG for vehicles that SGS/ETC tests. This would allow additional analysis to be performed similar to that described in Section 5.5.3.

6.0 Cost Estimation

The costs provided are ERG-loaded rough order of magnitude estimates obtained at the time this pilot study was conducted, based on standard contract terms and conditions. Actual costs may vary depending on the full-scale study objective, sample size, and final technical requirements. The scope of the full-scale study could be tailored to better meet funding requirements. These cost estimates are not a bid by ERG. Instead, the costs are provided to give potential funding organizations an idea of the funds that might be required to conduct the project as a function of scope. The costs presented here are based on the assumption that the datalogger would be capable of acquiring some specific enhanced PIDs of interest on many, but not all, vehicle combinations of year, make, model, and engine. This pilot study indicated that even that restricted goal would be a formidable task. The pilot study further indicated that acquisition of all enhanced PIDs of interest on all combinations of year, make, model, and engines would be a Herculean task.

6.1 Estimate of Sampling and Recruitment Costs

The estimated costs for sampling and recruitment are shown in Table 6-1 and are based on the description of recruitment given in Figure 4-2, which would be expected to produce one year of data on 200 vehicles. Some of the activities (Indexes A through F and I) in Table 6-1 have costs that are probably independent of the number of vehicles to be instrumented in the Main Study. However, costs for the other activities will change if the chosen vehicle sample size differs from 200 vehicles.

Table 6-1. Estimated Costs for Sampling and Recruitment Activities for the 200-Vehicle Scenario

Index	Item	Cost	Notes
A	Tentative recruitment tool design	$4,600	Draft texts for website, cover letter, brochure, interview script, hot buttons.
B	Cognitive test of effectiveness of incentive packages and cognitive testing of recruitment tools	$6,000	Test incentive packages to determine the incentive's effectiveness and understanding of the online and telephone tools and modify if necessary.
C	Finalize recruitment tool design	$6,400	Final texts for cover letter, brochure, interview script, hot buttons. Includes printing, packaging, mailing the 957 Advance Notification Packages.
D	Finalize and make project website operational	$7,900	Team/participant communications, incentive tracking, gamification, VIN check digit checker code.
E	Characterize national fleet	$14,400	National distributions of 11 variables.

Index	Item	Cost	Notes
F	Finalize Sampling Design	$4,800	Define sample size, stratification level bin definitions, representation approach.
G	Source of Participant Candidates[49]:		
	Option 1: Existing HHTS	$11,000	Crude estimate of cost based on expectation of collaboration and exchange of FE data to HHTS sponsor. Quote was not obtained. Actual cost could deviate substantially from this figure.
	Option 2: Knowledge Network HHTS	$253,000	Crude estimate of cost based on similar sized projects in other technical areas and expectation that cost will be more than Option 4. Quote was not obtained. Actual cost could deviate substantially from this.
	Option 3: SSRS Omnibus HHTS	$198,000	Crude estimate of cost based on similar sized projects in other technical areas and expectation that cost will be more than Option 4. Quote was not obtained. Actual cost could deviate substantially from this.
	Option 4: Main-Study-Specific HHTS	$145,000	Recruit 3,000 in lieu of NHTS. 75,000 address-based sample to dial 3,000 households to participate in the main study. Other budget assumptions: 20 minutes interview length, 62% response rate, incentive: 10 drawings for a $500 cash incentive.
	Option 5: Vehicle Registration Databases	$150,000	Option 5 costs are difficult to estimate since costs and requirements differ for each state. Although it is not likely all 50 states could be acquired, ERG expects at least 10 states could be acquired, and would attempt to obtain as many states as possible for this price estimate.
H	Prime Contractor Management of Source of Participant candidates	$9,600	
I	Select target vehicles from participant candidates	$48,000	Requires looking up tentative propulsion system, tentative FEEL values, zip-code-associated values.
J	Recruiting, online	$2,000	Based on Figure 4-2, 191 would sign up online.
K	Recruiting, telephone	$14,000	Based on Figure 4-2, expect to talk with 766 recruitment targets, interview lasting 15 minutes.
L	Characterize Participant Pool	$36,000	Requires looking up propulsion system knowing the VIN, FEEL values, zip-code-associated values, selecting vehicles to match national representation.

[49] Bids were not obtained for Options 1, 2, 3, and 5. These costs are just estimates based on what we estimate the industry might charge for this size project.

6.2 Estimate of Costs for Pre-Data-Collection Activities

The estimated costs for activities prior to field data collection data collection are shown in Table 6-2. These costs are independent of the number of vehicles to be instrumented in the Main Study. The costs in Table 6-2 for Indexes a and b are affected by the enhanced-PID capability of the datalogger assumed for these cost estimates.

Table 6-2. Estimated Pre-Data-Collection Costs

Index	Item	Cost	Notes
a	Final Datalogger assessment	$48,000	Includes assessment of adequacy of measurement of acceleration, road grade, hybrid battery state of charge, A/C compressor status as needed in FE assessment. Includes additional validation of FE accuracy determined from OBD parameters for a hybrid and a diesel propulsion system. This cost assumes that the datalogger acquires enhanced PIDs.
b	Identify and convert enhanced OBD parameters by manufacturer to units for FE quantification	$24,000	Includes identifying appropriate enhanced OBD parameters fuel rate, as well as for hybrid battery state of charge and A/C status by manufacturer. This cost assumes that the datalogger acquires enhanced PIDs.
c	Develop datalogger installation instructions	$6,600	In-box and on-line instructions.

The scopes for Indexes a (Final datalogger assessment) and b (Identify and convert enhanced OBD parameters by manufacturer to units for FE quantification) require some explanation. These items are necessary since they include several tasks that are required in order to perform the Main Study as currently envisioned: For example, as described in Section 5.2.1, even once the ability to log certain enhanced PIDs for a vehicle is obtained, many vehicles may not broadcast fuel rate directly but rather will report a value from which fuel rate may be calculated. For example, some vehicles may provide fuel injector pulse width, and therefore determination of fuel rate would require either obtaining fuel injector calibration curves or developing a correlation between fuel injector pulse width (at a certain fuel pressure) and fuel rate using a MAF-derived fuel rate during stoichiometric operation. Such a relationship would need to be found on a by-vehicle basis. In another example, instead of fuel rate, some type of injector volume estimate may be reported as an enhanced PID (as was the case for the analysis described in Section 5.5.2). If so, the vehicle manufacturer’s strategy for calculating fuel rate based on this injector volume estimate needs to be obtained and used to convert to a fuel rate. Also, as described in Section 5.5.2, our limited analysis indicated that the vehicle’s enhanced

PID injector-based fuel rate may be incorrect during certain types of operation, and additional investigation would be needed to better understand fuel rate accuracy estimates for these types of vehicles. Additionally, work remains to convert GPS and/or 3-dimensional accelerometer data into road grade estimates and to evaluate the accuracy of these road grade estimates calculated from this data. We do not regard these activities as optional under the current study design.

6.3 Estimate of Costs for Data Collection

The estimated costs for data collection are shown in Table 6-3 for a project that would collect data on a 200-vehicle sample over a one-year period. The costs for most data-collection activities will change if the chosen vehicle sample size differs from 200 vehicles. Several of the activities have "Lo" and "Hi" scopes to reflect the range of options that may be chosen. The low and high options for these activities will be used in Table 6-8 to estimate the range of costs to collect the data.

Table 6-3. Estimated Data Collection Costs for the 200-Vehicle Scenario

Index	Item	Cost	Notes
d	Configure datalogger for each vehicle	$40,000	Individual configuration may be beneficial. Use tracking system so that correct vehicle gets correctly configured datalogger. This cost assumes that the datalogger acquires enhanced PIDs.
e	Send dataloggers to participants	$22,000	Maximum estimated cost to send dataloggers for a 2lb package insured at $1K is $84.43. Destination was Berwick, ME. Cost includes datalogger packaging and handling. Based on Figure 4-8, expect to initially send dataloggers to 267 households.
f	Online and phone assistance with datalogger installations	$5,000	Develop online FAQs, answer the phone. Assume that 167 (50% of 333) install with just printed or online instructions, and 83 (25% of 333) install with over-the-phone assistance. Assume that the remainder will require in-the-field assistance (see next item).
g	Field assistance with datalogger installations	$10,000	Vendor provides in-the-field installation assistance. Assume 83 (25% of 333) field installations needed at $100 per visit.
h	Verify datalogger installations	$4,800=Hi	Write server code that uses cellular data to verify that dataloggers were installed.
		$0=Lo	If cellular data transmission is not chosen, the installation and operation of dataloggers cannot be verified.

Index	Item	Cost	Notes
i	Replace participants who experience installation failures	$10,000=Hi	If cellular data transmission indicates that dataloggers were not installed and installation assistance is not successful, then the original participant will be replaced with a participant from the participant pool. Send additional 67 dataloggers.
		$5,000=Lo	If cellular transmission is not chosen, some participants will report their inability to install datalogger. If installation assistance is unsuccessful, new participants will be chosen from the pool. However, any dataloggers that are not installed and are not reported as not installed or that are installed but are not recording data cannot be detected.
j	Maintain participants for one year	$4,500	Includes managing incentives, adding new panelists for dropouts, and other support for the 267 participants with successful installations.
k	Verify continued datalogger operation	$4,800=Hi	"Level 1 Validation": Server code that produces reports of datalogging activity (presence of data).
		$0=Lo	If cellular transmission is not chosen, it will not be possible to verify continued datalogger operation.
l	Ongoing data collection and review throughout study	$16,800=Hi	"Level 2 Validation": Assumes cell communication to server, download and review throughout study to ensure data is complete (not validation or QC).
		$0=Lo	If cellular transmission is not chosen, it will not be possible to review data.
m	Ongoing data processing, QC and validation	$21,600=Hi	"Level 3 Validation": Server code and engineering review to continuously evaluate data from each vehicle to ensure that it makes sense. This does not include an analysis of fuel economy.
		$0=Lo	If cellular transmission is not chosen, it will not be possible to review data.
n	Vehicle support during study	$31,000	Hands-on support for automotive problems, dead batteries, etc. This includes $25,000 dedicated to vehicle support by local vendors.

Index	Item	Cost	Notes
o	Run main study for one year	$120,000=Hi	General data handling and management prior to various validation steps, including development and management of Internet site to collect data, extraction of data to local server and backup procedures, daily tracking of incoming data, review of Level 1 and 2 validation results, resolution of technical issues that arise, QC of subcontractor activities, subcontractor management and support.
		$40,000=Lo	Process each of the HEM Data files (estimated 4,000 files for each of the vehicles). This is just dumping data from server and the associated processing. It does not include any tracking, phone calls, validation, or any of the activities listed in the cell above for Hi.
p	Datalogger removal and retrieval	$32,000	At end of study, getting all the loggers back. Expect that this will involve a call or postcard, packing and shipping return shipment materials (2 shipments), and communications to get the stranglers. Includes development of in-box and online removal instructions.
q	Online and phone assistance with datalogger removals	$1,300	Develop online FAQs, answer the phone. Assume that 167 (50% of 333) remove with just printed or online instructions, and 83 (25% of 333) remove with over-the-phone assistance. Assume that the remainder will require in-the-field assistance (see next item).
r	Field assistance with datalogger removals	$10,000	Vendor provides in-the-field installation assistance. Assume 83 (25% of 333) field removals needed costing $100 per in-person removal.
s	Incentive payments	$154,200=Hi	Incentives are based on 267 receiving a full $500 and 67 failed-installations receiving $100.
		$36,600=Lo	Incentives are based on 267 receiving a full $100 and 67 failed-installations receiving $100.
t	Vehicle parts and service	$11,000	To handle claims by participants that participation in the study damaged their vehicle.

The scope for Index d (Configure datalogger for each vehicle) requires some explanation. The cost estimate accounts for classifying and grouping each study vehicle by technology type in order to collect standard SAE J1979 PIDS (i..e, vehicles with MAF/narrow-band; MAF/wide-band; MAP/ narrow-band; MAP/wide-band; diesel, CAN vs. legacy, etc.) in order to standardize generic-PID acquisition. However, this task also includes collection of enhanced PIDs by make, model, model year, and engine. This will entail significantly more configuration effort, in particular, because enhanced PID data collection strategies differ by make, model, model year, and also by parameter. For example, A/C compressor status and hybrid battery state of charge are likely to be on different vehicle CAN networks and must be requested separately from the powertrain CAN module. Enhanced PID data collection is non-standardized and substantially more time consuming than generic PID data collection.

The scope for the "Hi" option of Index o (Run main study for one year) requires some explanation. While it might seem like the data in the Main Study will be collected automatically by unattended dataloggers, our experience suggests that some level of human vigilance will be required to help ensure that problems are quickly detected, recognized, and addressed so that the project has a reasonable chance of meeting completeness objectives. The level of labor that we have used for this estimate is equivalent to $1.65 per day per datalogger. Any support that can be automated would be automated, but development, refinement, and implementation of logic and programming to perform (and automate, as possible) day-to-day study operations and data collection activities requires time and effort. In addition, as with any study, in particular, large studies involving innovative and groundbreaking work with a large number of participants, we envision continued, ongoing direct support will be required to resolve issues that inevitably arise.

6.4 Estimate of Costs for Data Processing

The estimated costs for data processing are shown in Table 6-4 for a project that would collect data on a 200-vehicle sample over a one-year period. The costs tend to be independent of the number of vehicles to be instrumented in the Main Study. Development of a project relational database has a "Lo" and "Hi" scope to reflect the range of options that may be chosen. These low and high options will be used in Table 6-9 to estimate the range of costs for data processing. The costs in Table 6-4 for Indexes w and x are affected by the enhanced-PID capability of the datalogger assumed for these cost estimates.

Table 6-4. Estimated Costs for Data Processing for the 200-Vehicle Scenario

Index	Item	Cost	Notes
u	Linking meteorological data	$21,600	Estimates of meteorological data at the time and location of each vehicle will be obtained and linked to the datalogger data.
v	Linking fuel data, by season and region	$9,600	Fuel data for fuel economy estimates.
w	Development and analysis of FE results of study	$80,000	Apply appropriate fuel economy calculation strategy and assessment on a by-vehicle basis. This cost assumes that the datalogger acquires enhanced PIDs.
x	Development of project database	$24,000=Hi	A relational database of the datalogger and basic data will be provided. This cost assumes that the datalogger acquires enhanced PIDs.
		$5,000=Lo	The individual data files from the datalogger and a spreadsheet containing the basic data and the datalogger file names for each instrumented vehicle will be provided.
y	Compile and present interview information, data sheets, vehicle info	$3,000	Includes data files and a memo from NuStats with discussion of issues, lessons learned, and a brief analysis.
z	Analysis of comprehensive study data	not costed	This activity is not costed in this pilot.

6.5 Datalogger Costs

This section lists cost estimates to procure a datalogger that would be capable of acquiring in-use data as described in the previous subsections.

6.5.1 HEMData DAWN Mini

Table 6-5 provides ERG-loaded cost estimates for the HEMData DAWN Mini, as well as various costs for optional enhancements.

For any datalogging study, a greater number of dataloggers need to be purchased than the targeted number of complete vehicle datasets to be obtained in order to cover necessary participant oversampling and equipment failures and malfunctions. As described near the end of Section 4.2, for the 200-vehicle plan, which would target a minimum of 200 successful year-long instrumentations, 267 vehicles would need to be recruited and have dataloggers initially successfully installed and collecting or transmitting data to account for participant attrition during the one-year period. Reasons for attrition could include datalogger malfunction, vehicle accident, vehicle sale, and owner dissatisfaction with the project, as well as a variety of unexpected events that occur in any field project. Implementation of that plan requires 267 dataloggers (see Figure 4-2) ready to go at the beginning of the instrumentation phase. Any dataloggers that are returned when a vehicle ceases participation could be used again to maximize the size of the instrumented sample. Proportionately, 1068 loggers would be needed for the 800-vehicle study. Using the without-cellular datalogger prices from Table 6-5, that yields $234,000 (=267*$875) for the 200-vehicle study and $607,000 (=1068*$568) for the 800-vehicle study.

Table 6-5. HEMData DAWN Mini Costs

Item	Cost	Notes
HEMData DAWN Mini costs, by quantity		
1-4 base units, cost each	$2200	These costs are for the base unit with GPS, but with no cellular capability. HEM Data reports legacy protocol capability, accelerometer functionality and internal temp will be available in the fall of 2013 at no additional cost.
5-9 base units, cost each	$1790	
10-19 base units, cost each	$1490	
20-49 base units, cost each	$1350	
50-99 base units, cost each	$1170	
100-199 base units, cost each	$1030	
200-499 base units, cost each	$875	
500-999 base units, cost each	$568	
HEMData DAWN processing software	$640	Software purchase is per PC, not logger
Cellular communication service, per logger		
1-4 units, cost each (hardware)	$550	Cellular agreement still being finalized with carrier, costs to be refined as more info becomes available
5-9 units, cost each (hardware)	$550	
10-99 units, cost each (hardware)	$440	
100-199 units, cost each (hardware)	$330	
200-299 units, cost each (hardware)	$280	
Monthly cell communication service	$40	Est. depends on carrier and data quantity
Internet data repository (one-time fee)	$1300	One-time setup costs for simple cellular upload, and download functionality (either unprocessed (raw message) or processed (CSV)). No ongoing costs.
Addition of enhanced PID capability, by OEM[50]		
Chrysler / Dodge / Jeep	$16,300	
Ford	$4,600	
GM	$84,400	
Honda / Acura	$11,100	
Mazda	$6,500	Enhanced PIDs only on 2007 and newer
Nissan / Infiniti	$5,900	
Toyota / Lexus / Scion	$5,100	

[50] Costs for manufacturers other than those shown in this table are not available at this time, approximately one month required for addition of each vehicle manufacturer. These are one-time costs, not per datalogger.

If cellular transmission capability is desired with the dataloggers, costs for adding cellular transmission hardware to the dataloggers and costs for cellular transmission are incurred. For the 200-vehicle plan, as described in Section 4.2, since 267 dataloggers would initially be sent to participants, 267 cellular communication accounts would also be needed initially. In the unlikely case that all 267 vehicles and their dataloggers remain participating for the full year, then the 200-vehicle study will have collected data on 267 vehicles. If during the year a vehicle stops participating and project management decides not to replace the lost vehicle, then the decision can be made to terminate the cellular communication account.

The 200-vehicle study cellular cost for 1 year is $201,000, which is made up of $280/datalogger for hardware plus $39/datalogger per month for cellular service plus the one-time Internet data repository fee of $1,300. The 800-vehicle study cellular cost for 1 year is $767,000, which is made up of $250/datalogger for hardware plus $39/datalogger per month for cellular service plus the one-time Internet data repository fee of $1,300.

6.5.2 LiveDrive i2d

Table 6-6 provides ERG-loaded cost estimates for the LiveDrive i2d logger. No costs are currently available for enhanced data collection on this logger.

Table 6-6. LiveDrive i2d Costs

Item	Cost	Notes
Rough cost for approx 200-300 units (each)	$195	Units already include cell communication
Communication service (monthly)	$26	For 10 MB data, LiveDrive reports this should be adequate
Addition of enhanced PID capability, by OEM		
Enhanced PID data collection is not currently an option with the LiveDrive i2d logger		

6.5.3 ERG Logger

ERG developed a rough order of magnitude cost estimate of $300 per logger for the hardware associated with various functions of an OBDII datalogger. This estimate does not include any development, test, or assembly costs other than those associated with the printed circuit board assembly. This would be a datalogger attached to the DLC using an electrical cable with a physical design similar to the LiveDrive i2d unit and would have the features listed in Table 5-6, except enhanced PIDs data collection capability which would be additional cost, likely similar to the cost for adding enhanced PIDs to the HEMData DAWN Mini. It may be possible to develop a smaller logger which mounts directly onto the DLC, although this would likely increase overall unit costs. Also, the datalogger would not have Bluetooth or Wi-Fi unless the need arose. The datalogger would have cellular communication capability at market-competitive monthly rates. Data would be packaged in binary format for storage and transmission to minimize data storage and transmission costs. This cost estimate is based on a volume of about 100 pieces. However, it is important to understand this estimate does NOT include development, testing, or manufacturing costs, which would significantly add to the cost of the logger. This additional cost information can be provided as we move forward.

6.6 Cost Summary for Two Sample Size Scenarios: 200 and 800 Vehicles

A summary of the costs for proceeding beyond this pilot study are presented in this section. The Main Study work would be made up of three parts: preparation, data collection, and data processing. The preparation work is needed to prepare for the data collection effort. The costs for the preparation study are given in Table 6-7. The activities included in Sample and Recruitment Design and Datalogger Design must be done for the Main Study to be performed; they are not optional. The Other Analyses, which refer to the future proposed analyses in Section 5.6 are optional but recommended.

Table 6-7. Estimated Costs for Preparation for Data Collection

Task	Detail	Low	High
Preparation for Main Study	Sample and Recruitment Design[51]	44,000	44,000
	Datalogger Design[52]	79,000	79,000
	Other Analyses[53]	0	not costed
	Total	**123,000**	**≥ 123,000**

A summary of estimated costs for the data collection portion of the Main Study is presented in Table 6-8 for 200 and 800 vehicles and assumed low and high cost options for each of those two sample sizes. For some of the major costs, vendors were not contacted. Accordingly, the costs in this section are just indications of costs for a main study, which are based on information gleaned from conversations with people in the industry, as well as experience in doing work of a similar nature in the past. All costs include using only the HEM Data DAWN Mini datalogger, since the i2d datalogger was not able to be demonstrated yet as a viable contender. All costs also include acquiring the enhanced-PID databases for the vehicle manufacturers listed at the bottom of Table 6-5.

[51] Consists of activities described inTable 6-1 A, B, C, D, E, and F.
[52] Consists of activities described inTable 6-2 a, b, and c.
[53] Other analyses include any of the studies described in Section 5.6 Proposed Future Analysis or any other studies.

Table 6-8. Estimated Data Collection Costs for 200- and 800-Vehicle Scenarios

Task	Detail	200 Vehicles		800 vehicles	
		Low	High	Low	High
Recruitment and Sampling	Fleet characterization and filtering[54]	84,000	84,000	192,000	192,000
	Participant interaction and management[55]	26,000	26,000	84,000	84,000
	Sources of drivers/vehicles[56]	11,000	253,000	44,000	495,000
	Total	**121,000**	**363,000**	**320,000**	**771,000**
Data Collection	Tailoring for each vehicle[57]	40,000	40,000	160,000	160,000
	Datalogger logistics + maintenance[58]	172,000	266,000	687,000	826,000
	Data management[59]	0	38,000	0	154,000
	Incentives[60]	37,000	154,000	147,000	617,000
	Total	**249,000**	**498,000**	**994,000**	**1,757,000**
Datalogger	Datalogger basic hardware[61]	234,000	234,000	607,000	607,000
	Cellular data + hardware[62]	0	201,000	0	767,000
	Enhanced PID costs[63]	134,000	134,000	134,000	134,000
	Total	**368,000**	**569,000**	**741,000**	**1,508,000**
	Total	**738,000**	**1,430,000**	**2,055,000**	**4,036,000**

Table 6-9. Estimated Data Post-Processing Costs for 200- and 800-Vehicle Scenarios

Task	Detail	200 Vehicles		800 vehicles	
		Low	High	Low	High
Data Processing	Acquire/Link associated data[64]	31,000	31,000	31,000	31,000
	Presentation of data[65]	83,000	83,000	123,000	123,000
	Data archiving[66]	5,000	24,000	5,000	24,000
	Total	**119,000**	**138,000**	**159,000**	**178,000**

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[54] Consists of activities described inTable 6-1 I and L.
[55] Consists of activities described inTable 6-1 H, J, and K.
[56] Consists of activities described inTable 6-1 G.
[57] Consists of activities described inTable 6-3 d.
[58] Consists of activities described inTable 6-3 e, f, g, h, i, j, k, n, o, p, q, r, and t.
[59] Consists of activities described inTable 6-3 l and m.
[60] Consists of activities described inTable 6-3 s.
[61] See Section 6.5.1 for details.
[62] See Section 6.5.1 for details.
[63] See bottom of Table 6-5.
[64] Consists of activities described inTable 6-4 u and v.
[65] Consists of activities described inTable 6-4 w and y.
[66] Consists of activities described inTable 6-4 x.

Within each of the two sample size scenarios, we have tried to estimate different costs for sub-scenarios that we call "Low" and "High." While these low and high costs give some indication of the range of costs that are possible by making significant changes to the project scope, other modifications to the scope may produce project costs that are outside the range defined by the low and high values.

A summary of the data processing costs is provided in Table 6-9.

The results shown in Tables 6-7, 6-8, and 6-9 indicate that, for the listed scope, the expected cost to acquire one year of second-by-second data is from about $3,700 to $7,200 per vehicle for a 200-vehicle sample and is from about $2,600 to $5,000 per vehicle for an 800-vehicle sample, plus pre- and post-processing costs of about $1,300 per vehicle for a 200-vehicle sample and $400 per vehicle for an 800-vehicle sample. These per-vehicle costs are equivalent to the cost of a few chassis dynamometer tests.

7.0 Appendices

Appendix A
Technical Approach for Stratified Sampling

The measure of precision we would use is the standard error of the mean annual fuel consumption for the average fleet vehicle. The standard error of a quantity is the standard deviation of its error. We want to allocate the data points to be collected among the strata so as to minimize the standard error of the mean annual fuel consumption.

Suppose the total size of the sample of vehicles to be instrumented has a value n, which has been selected. The subject of this appendix pertains to the benefits that can be gained by stratification. We first discuss the issues qualitatively, and subsequently we present the equation for the optimal sample size by stratum. The equations pertaining to stratified sampling discussed in this appendix are presented by Gilbert (1987).

One factor is the fraction of the population that falls in a given stratum. The larger this fraction is, the more data points one would like to take from the stratum. This concept is conceptually clear and will not be elaborated.

A second factor is the variability in the stratum. It can be shown mathematically that it is advantageous to collect more data points from strata with large variability than from strata with small variability.

A simple, strictly hypothetical example illustrates this idea conceptually. Suppose there are only two strata, stratum one has no variability at all, and stratum two contains non-negligible variability. If one data point is collected from stratum one, the annual fuel consumption for that stratum is known exactly. Any more data points taken from that stratum are wasted; no additional information is gained.

However, the uncertainty in the mean annual fuel consumption for stratum two becomes more and more precise as the number of data points taken from that stratum increases. Thus, in this example, it would be beneficial to take one data point from the stratum with no variability and the rest of the points from the stratum with variability.

This example is hypothetical, but it illustrates the fact that it is advantageous to take more data points from strata with a higher degree of variability. In the real situation of interest, the annual fuel consumptions in all strata have variability, but the degree of variability differs from stratum to stratum.

We are now ready to state the equation for the optimal sample size for a given stratum:

$$n_h = \frac{n\, W_h\, \sigma_h}{\sum_{h=1}^{L} W_h\, \sigma_h}$$

where

n_h = the sample size in stratum number h,
n = the total sample size for all strata,
W_h = the fraction of the actual population that falls in stratum h,
L = the number of strata, and
σ_h = the standard deviation of the annual fuel consumptions in stratum h.

This equation follows conceptual guidelines. The number of points taken from a stratum is directly proportional to the fraction of the population comprised of that stratum (the fraction is W_h). Also, the number of points from a stratum is directly proportional to σ_h, which is a measure of the variability in the stratum.

The estimate of the population mean, $\bar{x}_{pop}$, is the weighted mean of the stratum means, $\bar{x}_h$:

$$\bar{x}_{pop} = \sum_{h=1}^{L} W_h\, \bar{x}_h$$

The point here is that the strata are not sampled proportionately to their actual representation in the population. If a simple arithmetic average of the complete stratified sample were calculated, the different strata would be weighted disproportionately to their representation in the population, and a biased average would result. The weighting scheme in the calculation of $\bar{x}_{pop}$ accounts for the nature of the sample and produces an unbiased estimate of the population mean. The formulation here produces the unbiased estimate of the population mean with the minimum error variance, given the total sample size, n. The standard error of the mean is the square root of its error variance.

The standard error of this weighted mean estimate is as follows:

$$\sigma_{\bar{x}_{pop}} = \sqrt{\sum_{h=1}^{L} W_h^2 \frac{\sigma_h^2}{n_h}(1-f_h)}$$

where f_h is the number of data points in stratum h divided by the population size of this stratum.

The factor $(1-f_h)$ accounts for the finitude of the population in stratum h. If the sample sizes are small compared to the sizes of the strata in the population, this factor can be ignored. The factor $(1-f_h)$ can be ignored (set to 1) in the calculations since the size of the vehicle sample will be much smaller than the size of U.S. vehicle fleet.

In practice the true standard deviations, σ_h, are not known and are estimated on the basis of historical data that exist before the planned stratified sampling effort. The sample standard deviation, s_h, based on a sample, $x_{h,i}$, i=1 to m, is:

$$s_h = \sqrt{\frac{\sum_{i=1}^{m} (x_{h,i} - \bar{x}_h)^2}{m-1}}$$

where $\bar{x}_h$ is the arithmetic mean.

Appendix B
Model 11 Performance Plots

ERG's subcontractor SGS ETC performed in-laboratory on-chassis dynamometer testing of a 2009 Saturn Outlook using several different test cycles. These tests were conducted at the SGS ETC laboratory in Aurora, Colorado, and the cycles used were the EPA standard city cycle (FTP75), the EPA standard highway fuel economy cycle (HFET), and the aggressive drive cycle (US06). Fuel consumption and emissions were measured on a second-by-second basis during each test, and standard protocols were used to determine the second-by-second fuel consumption and emissions over each drive cycle. Standard SAE J1979 OBDII data was also logged throughout the testing using the HEM Data DAWN Mini datalogger. The analysis, which is described in Section 5.5.3, compares fuel rate calculated from dynamometer data with fuel rate calculated from OBD data.

The 2009 Saturn Outlook was equipped with a 3.6L V6 gasoline direct injection (GDI) engine. The vehicle was equipped with a mass air flow sensor and a narrow-band oxygen sensor. The fuel used was EPA Tier II certification fuel with no ethanol. The specific gravity was 0.7389, and the API Gravity was 60.0.

During all vehicle operation on the dynamometer, the HEM Data logger was installed on the Saturn's OBD port. The dynamometer testing produced two datasets. One set was obtained from the HEM Data logger and included data from standard PIDs. The other set was obtained from the dynamometer test cell and included measurements from the dynamometer and from the constant volume sampling system.

The 2009 Saturn Outlook was tested on a chassis dynamometer over three cycles: the HFET, US06, and FTP75 driving schedules. The FTP75 test was made up the traditional three bags: a cold start for Bag 1, which was immediately followed by Bag 2, then a 600-second soak, which was followed by Bag 3. Two HFETs and two US06s were run with the first of each pair being used to warm up the vehicle for the dynamometer data acquisition on the second of each pair.

The following figures compare fuel rate calculated from dynamometer measurements of exhaust concentrations and flow rate, modeled fuel rate based on OBD mass air flow and OBD commanded equivalence ratio, an indicator of fuel cut-off based on OBD commanded equivalence ratio, an indicator variable of cold starts based on OBD commanded equivalence ratio, and vehicle speed. See the description in Section 5.5.3 for detailed descriptions of the variables shown in the following figures.

Figure B-1. HFET Part 1

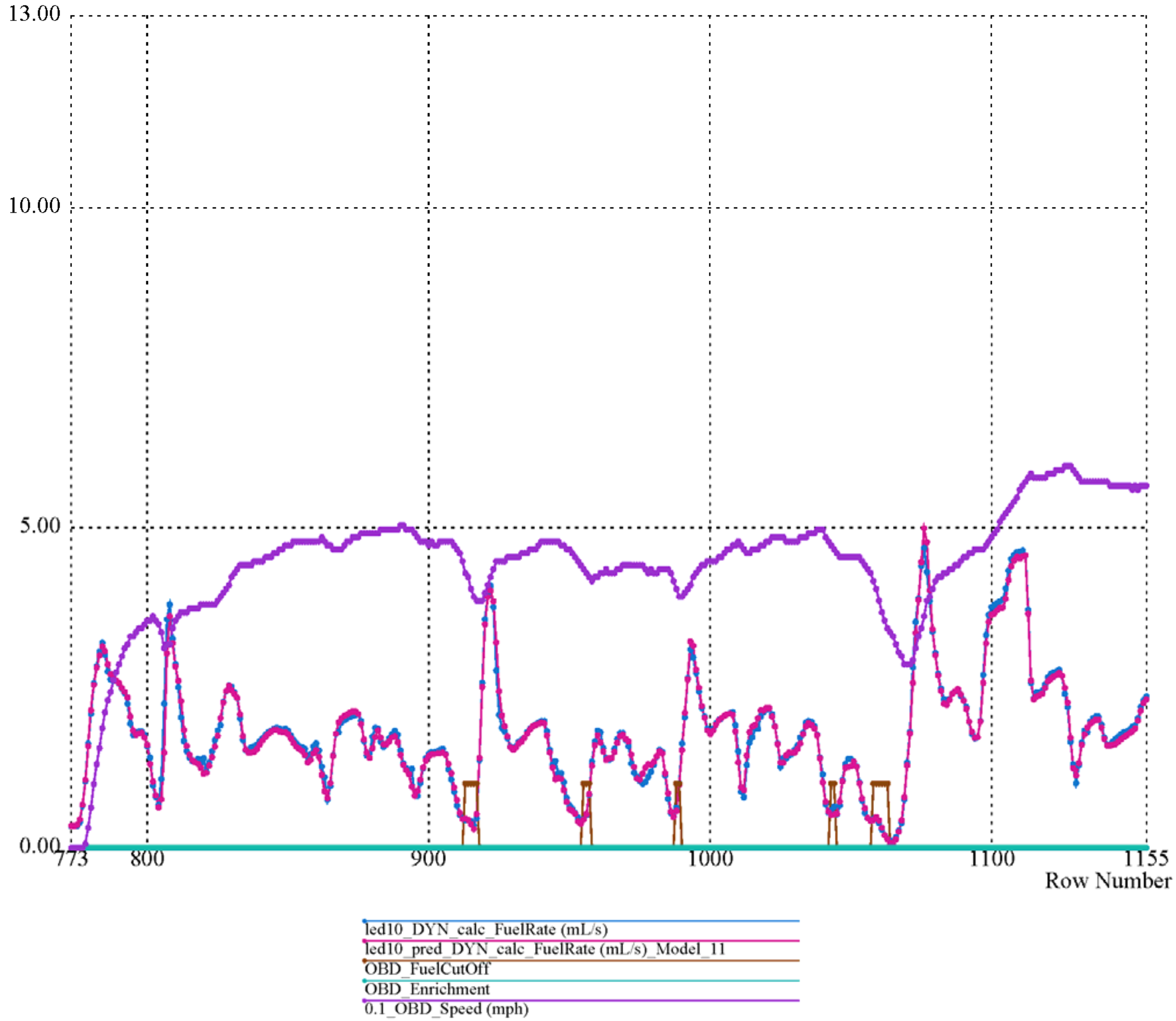

Figure B-2. HFET Part 2

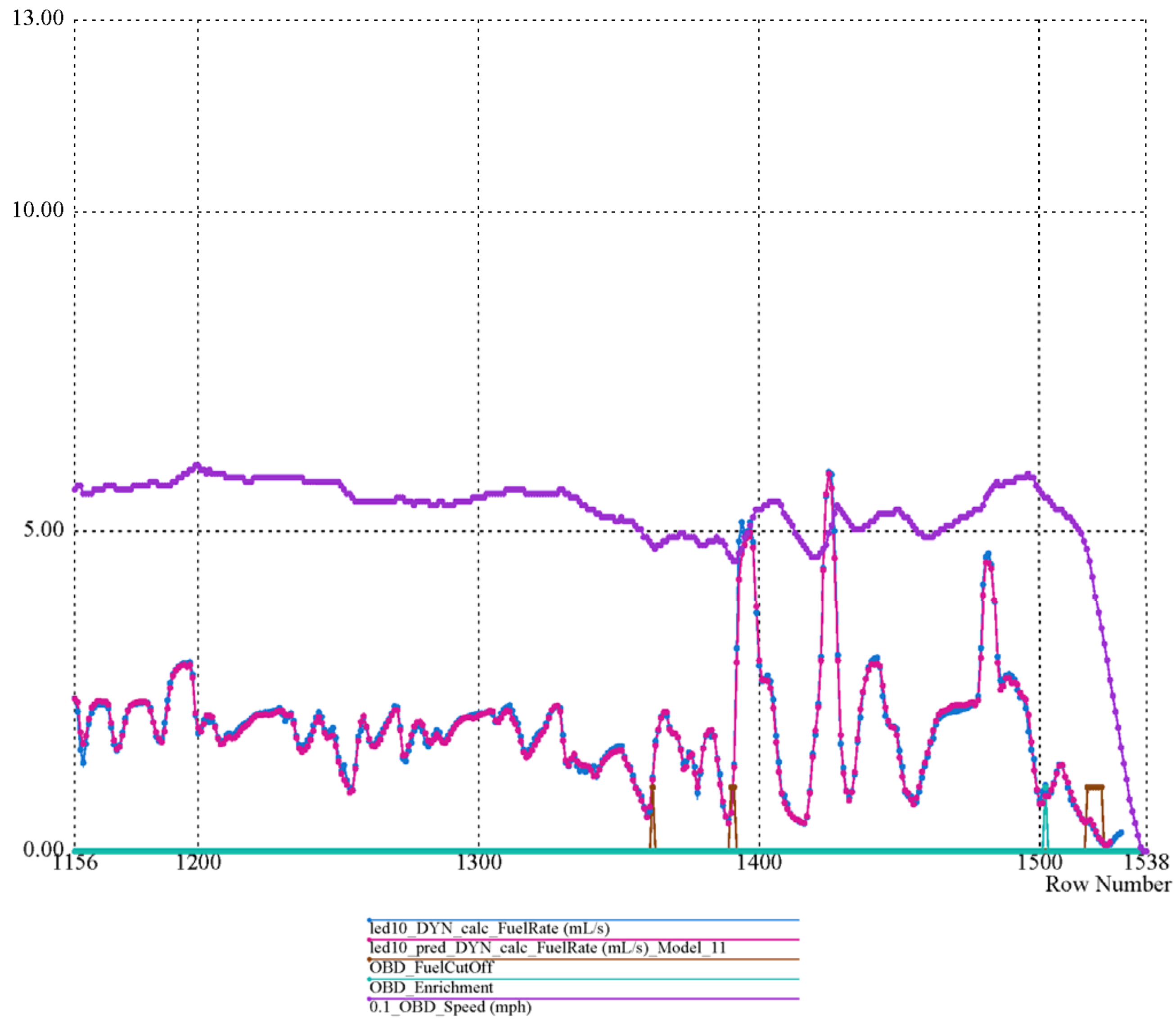

Figure B-3. US06 Part 1

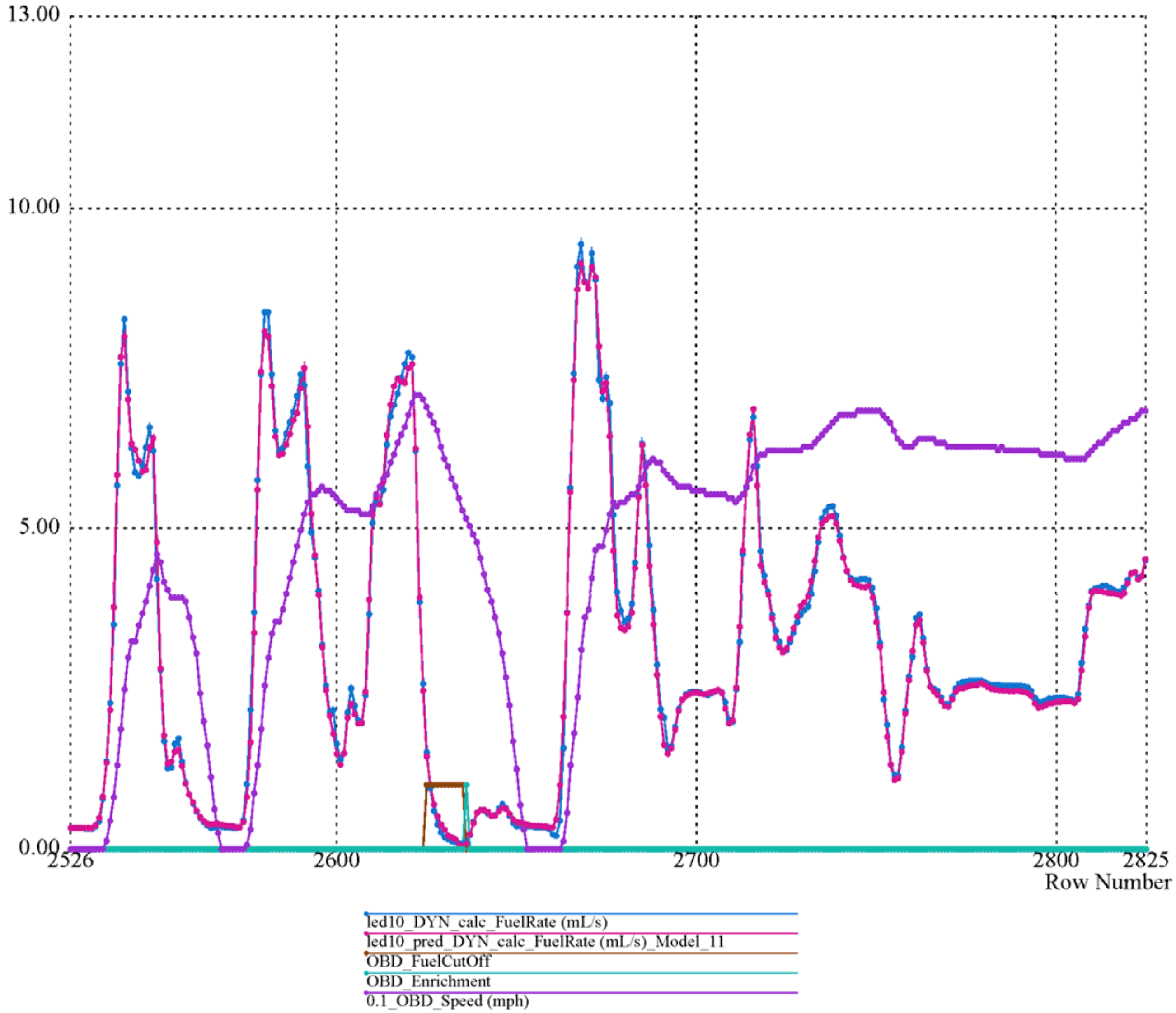

Figure B-4. US06 Part 2

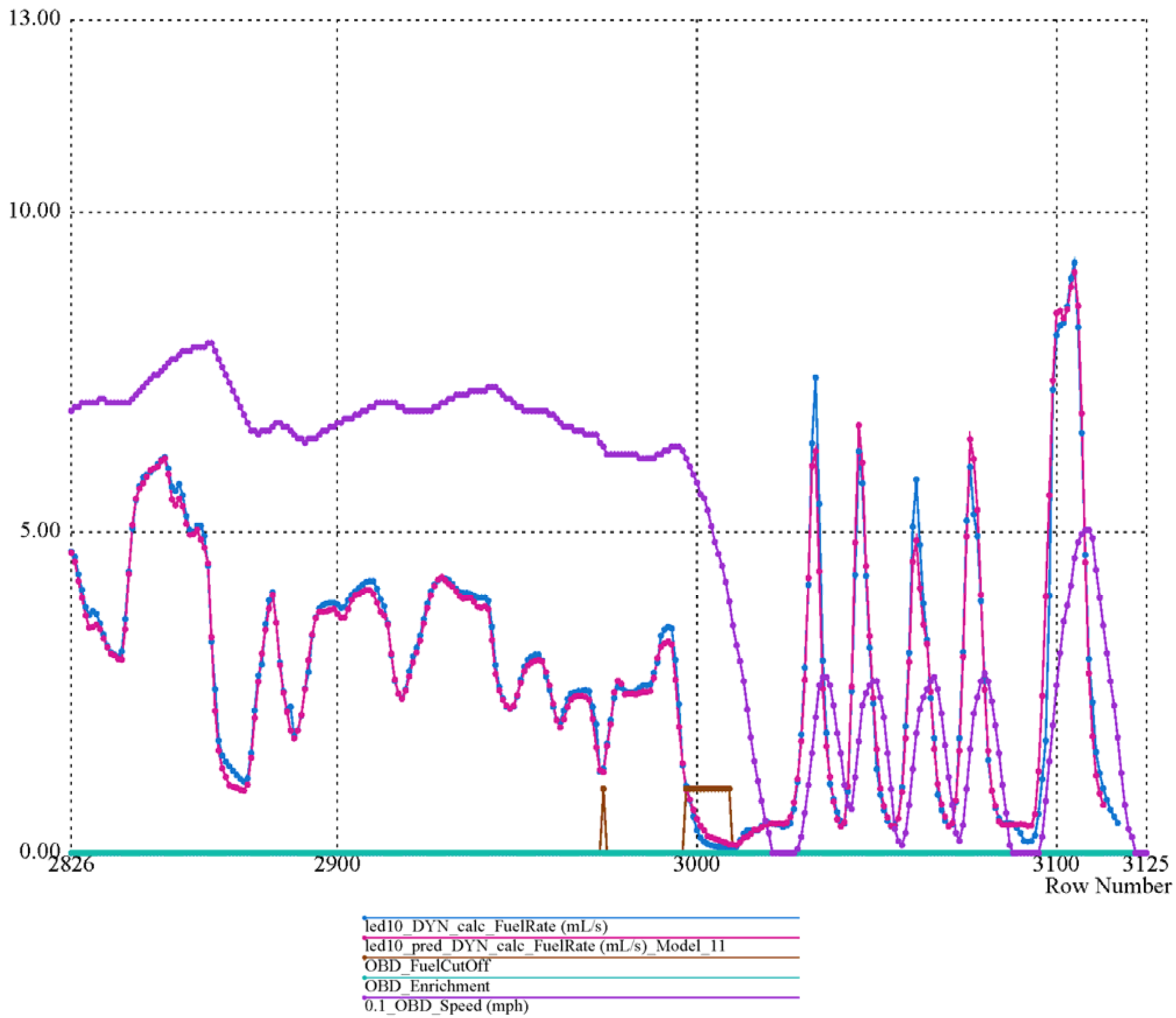

Figure B-5. FTP75 Bag 1 Part 1

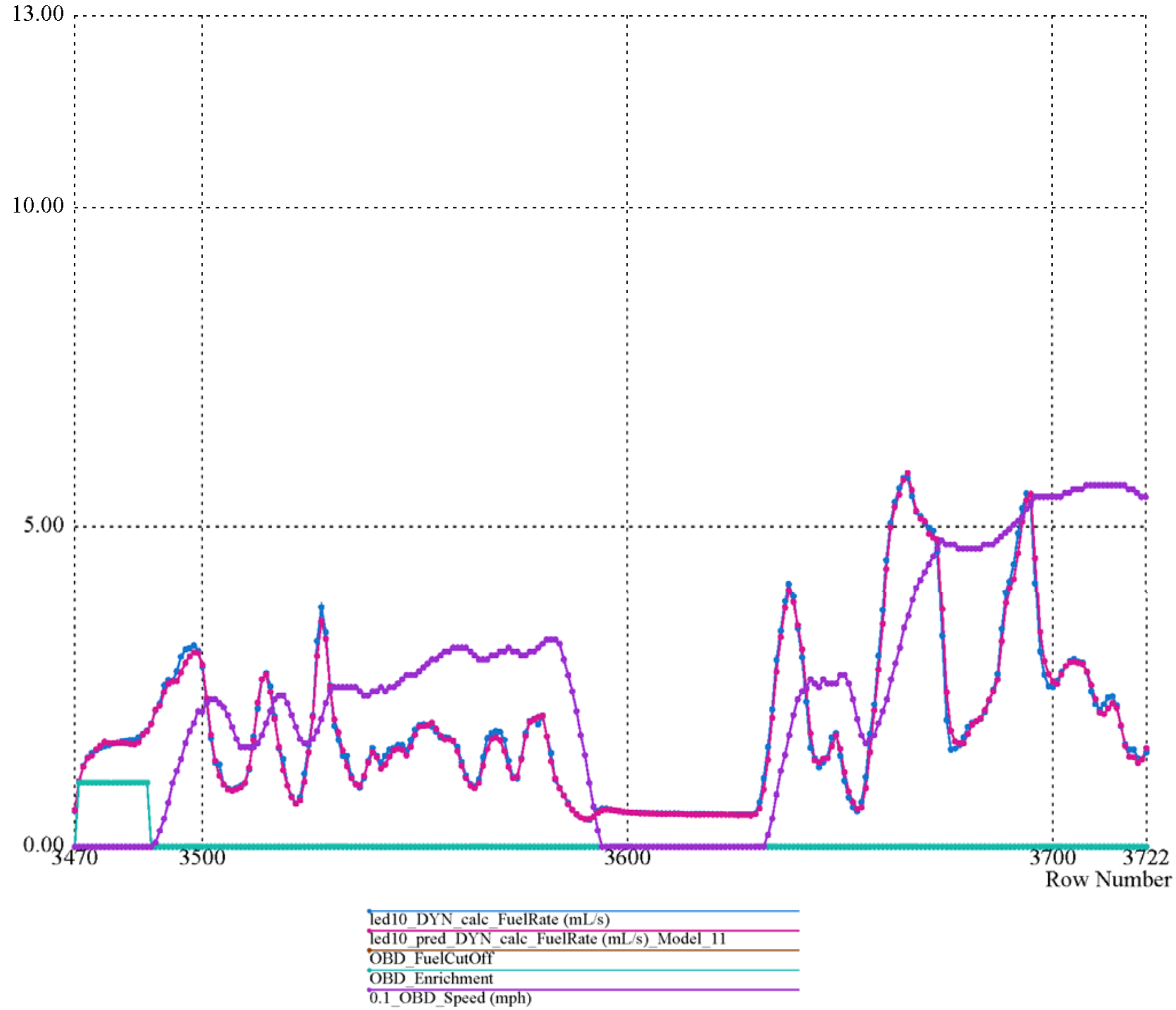

Figure B-6. FTP75 Bag 1 Part 2

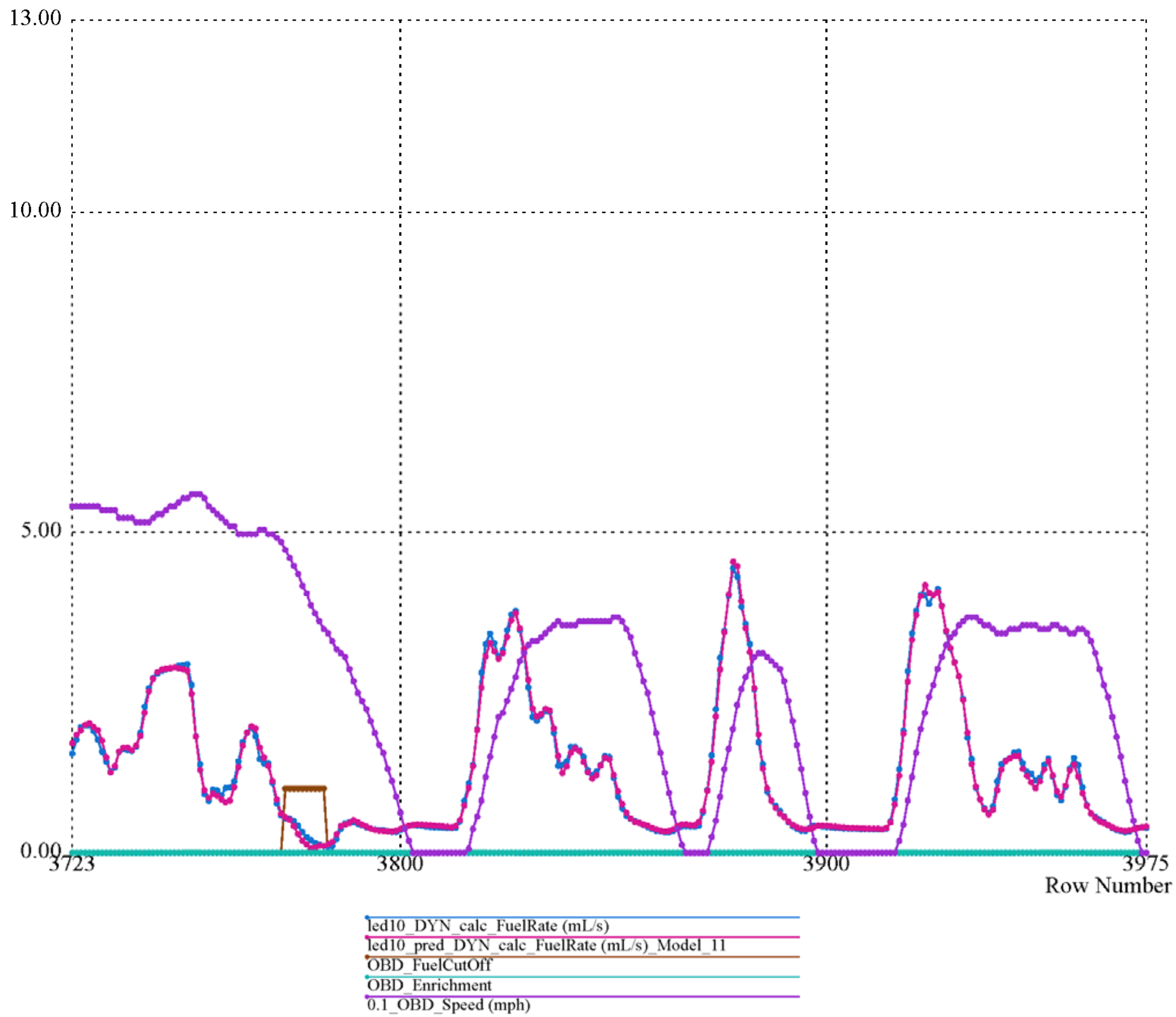

Figure B-7. FTP75 Bag 2 Part 1

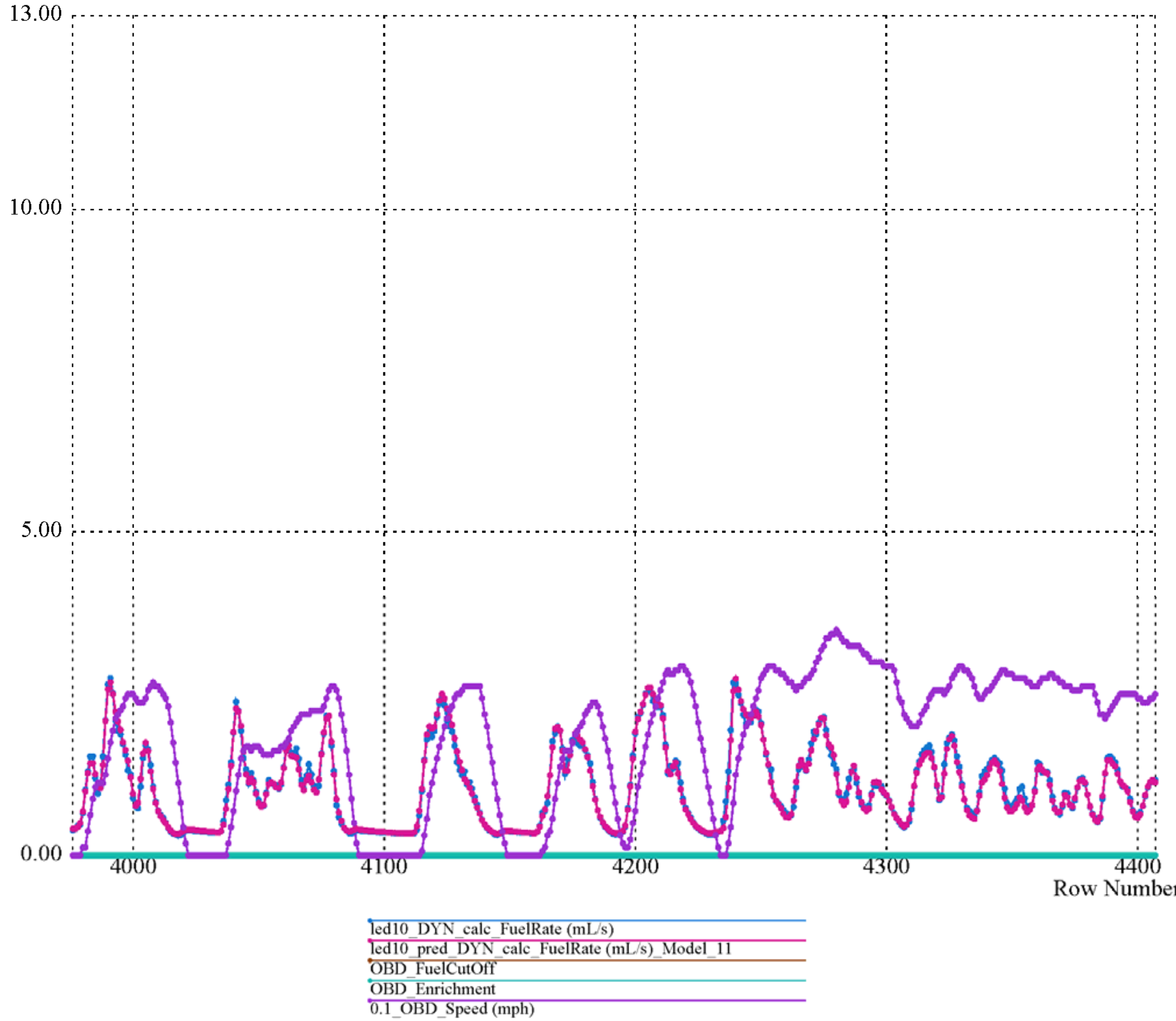

Figure B-8. FTP75 Bag 2 Part 2

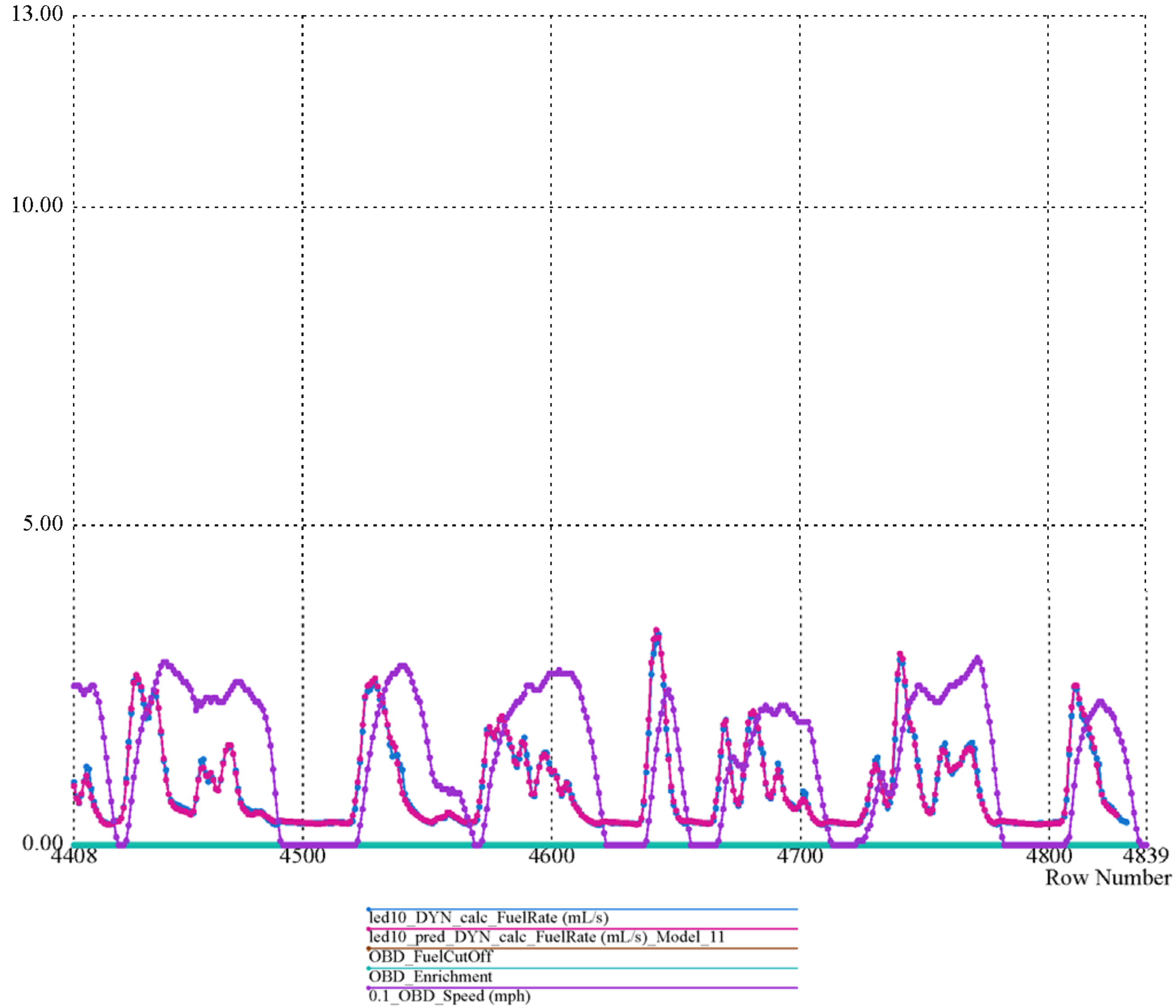

Figure B-9. FTP75 Bag 3 Part 1

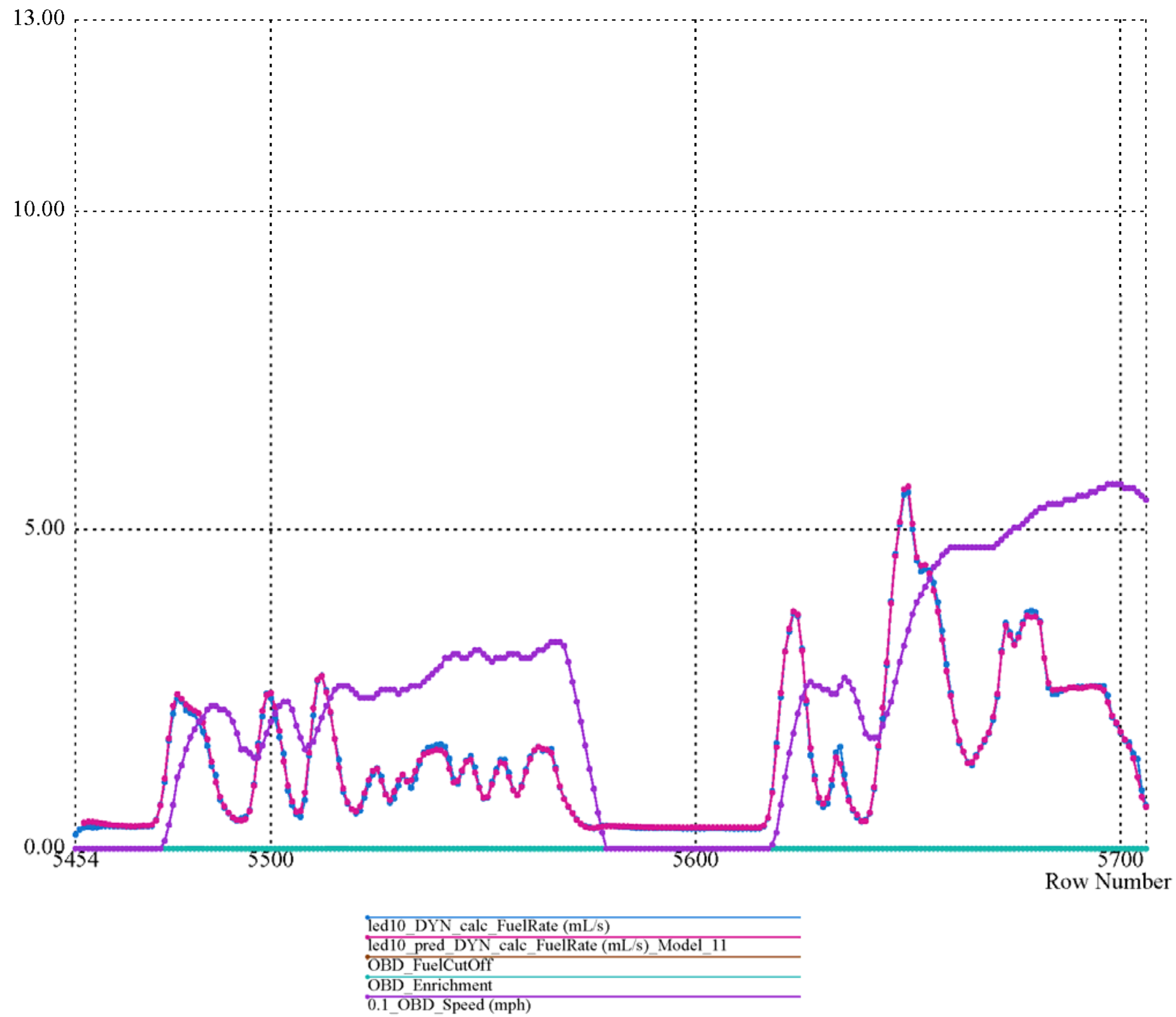

Figure B-10. FTP75 Bag 3 Part 2