THESIS

METHODS TO ANALYZE LARGE AUTOMOTIVE FLEET-TRACKING DATASETS WITH APPLICATION TO LIGHT- AND MEDIUM-DUTY PLUG-IN HYBRID ELECTRIC VEHICLE WORK TRUCKS

Submitted by

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ABSTRACT

METHODS TO ANALYZE LARGE AUTOMOTIVE FLEET-TRACKING DATASETS WITH APPLICATION TO LIGHT- AND MEDIUM-DUTY PLUG-IN HYBRID ELECTRIC VEHICLE WORK TRUCKS

This work seeks to define methodologies and techniques to analyze automotive fleet-tracking big data and provide sample results that have implications to the real world. To perform this work, vehicle fleet-tracking data from Odyne and Via Plug-in Hybrid Electric Trucks collected by the Electric Power Research Institute (EPRI) was used. Both CAN-communication bus signals and GPS data were recorded off of these vehicles with a second-by-second data collection rate. Colorado State University (CSU) was responsible for analyzing this data after it had been collected by EPRI and producing results with application to the real world.

A list of potential research questions is presented and an initial feasibility assessment is performed to determine how these questions might be answered using vehicle fleet-tracking data. Later, a subset of these questions are analyzed and answered in detail using the EPRI dataset.

The methodologies, techniques, and software used for this data analysis are described in detail. An algorithm that summarizes second-by-second vehicle tracking data into a list of higher-level driving and charging events is presented and utility factor (UF) curves and other statistics of interest are generated from this summarized event data.

In addition, another algorithm was built on the driving event identification algorithm to discretize the driving event data into approximately 90-second drive intervals. This allows for a regression model to be fit onto the data. A correlation between ambient temperature and

equivalent vehicle fuel economy (in miles per gallon) is presented for Odyne and it is similar to the trend seen in conventional vehicle fuel economy vs. ambient temperature. It is also shown how ambient temperature variations can influence the vehicle fuel economy and there is a discussion about how changes in HVAC use could influence the fuel economy results.

It is also demonstrated how variations in the data analysis methodology can influence the final results. This provides evidence that vehicle fleet-tracking data analysis methodologies need to be defined to ensure that the data analysis results are of the highest quality. The questions and assumptions behind the presented analysis results are examined and a list of future work to address potential concerns and unanswered questions about the data analysis process is presented. Hopefully, this future work list will be beneficial to future vehicle data analysis projects.

The importance of using real-world driving data is demonstrated by comparing fuel economy results from our real-world data to the fuel economy calculated by EPA drive cycles. Utility factor curves calculated from the real-world data are also compared to standard utility factor curves that are presented in the SAE J2841 specification. Both of these comparisons showed a difference in real-world driving data, demonstrating the potential utility of evaluating vehicle technologies using the real-world big data techniques presented in this work.

Overall, this work documents some of the data analysis techniques that can be used for analyzing vehicle fleet-tracking big data and demonstrates the impact of the analysis results in the real world. It also provides evidence that the data analysis methodologies used to analyze vehicle fleet-tracking data need to be better defined and evaluated in future work.

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ACKNOWLEDGEMENTS

Much of this work was only possible due to the group efforts of a large number of people. In addition to my own hard work, many other individuals contributed this body of work and it would not have been possible without their help.

First of all, I would like to thank the team at The Electric Power Research Institute (EPRI) who collected and managed the vehicle tracking data that was used to perform this work. This work would have not been possible without access to their secure dataset, technical support, and administrative support. Individuals at EPRI I would specifically like to thank who worked with us closely are Marcus Alexander, Mark Kosowski, Jamie Dunkley, Morgan Davis, and Norm McCollough.

I would also like to thank Green Mountain Software Company, who is contracted by EPRI to manage the data, for providing general support and information for the dataset. Much of this work would not have been possible without their technical support as well.

Next, I would like to thank Zachary Wilkins, who was an undergraduate research assistant who worked with me on one of our EPRI contracts for the Medium-Duty Truck Data. He was responsible for developing a large portion of the Driving and Charging events Identification algorithm described in Section 4. This work was also presented in a paper to the Electric Vehicle Symposium 29 in Montreal Quebec [1]. In addition, Zack wrote the majority of the MATLAB code to implement this algorithm, based on framework that I had previously developed and which is described in Section 2. This part of the work would not have been successful without his hard work and intellect and he was a major contributor to the work presented in Section 4.

In Section 5, Mike Reid and Joseph Minicucci (aka Joe) were responsible for writing some of the software to implement the vehicle efficiency calculation algorithm that I developed. Among other contributions, Mike Reid rewrote much of the data analysis framework that is described in Section 2 and helped implement my data filtering and splitting algorithm using MATLAB. Joseph Minicucci did a fantastic job of implementing the MapReduce algorithm I developed into actual Java code. In addition, both Mike and Joe showed me a ton of new Computer Science and Java tricks during our class project that I would not have stumbled across on my own. This part of the project was very challenging and I did not have time to write all of this code on my own. I am thankful for all of Mike and Joe's hard work.

In addition, I would like to thank Dr. Sangmi Pallickara in the Computer Science Department here at Colorado State University for admitting me into her CS435 Big Data class. This class is where we started the work presented in Section 5 for our class project. I did not have most of the pre-requisite classes that Computer Science majors are normally required take before enrolling in this class, but Dr. Pallickara believed in me and helped me get admitted to the class regardless. Without taking this course, I would not have learned how to develop software for the Hadoop MapReduce framework that is used for some of the data analysis described in Section 5. Dr. Pallickara also did not make a mistake by letting me into this class despite my lack of background knowledge. I earned an A in the course on the same grading scale as everyone else. I thank Dr. Pallickara for giving me the opportunity to build my own success.

In the Mechanical Engineering Department, I would also like to thank Megan Kosovski who is the graduate program coordinator. She was a great source of information and support to resolve pretty much any academic, registration, or other administrative issue while I was at

Colorado State University. She genuinely cares about making sure everyone in her program can be successful and that is one of the reasons that she is so good at her job.

Finally, I would like to thank my research advisor Dr. Thomas Bradley for supporting me while I pursued this research. Dr. Bradley gave me the opportunity to conduct this research and receive the funding to earn my Master's Degree and for this I am very thankful. In addition to providing invaluable insight and advice to make this work possible, he is also an extraordinarily kind and positive human being. It is hard to catch Dr. Bradley without a smile on his face. In addition, I am also very thankful that Dr. Bradley was able to fill out all of the administrative paperwork and put up with me for two whole years. It was a pleasure to work under him during my time here at Colorado State University.

Without collaboration between all of these folks, much of this work would not have been possible. Although I contributed a large amount of my personal time, energy, and ideas towards the project, there would have been only so much that I could have accomplished on my own.

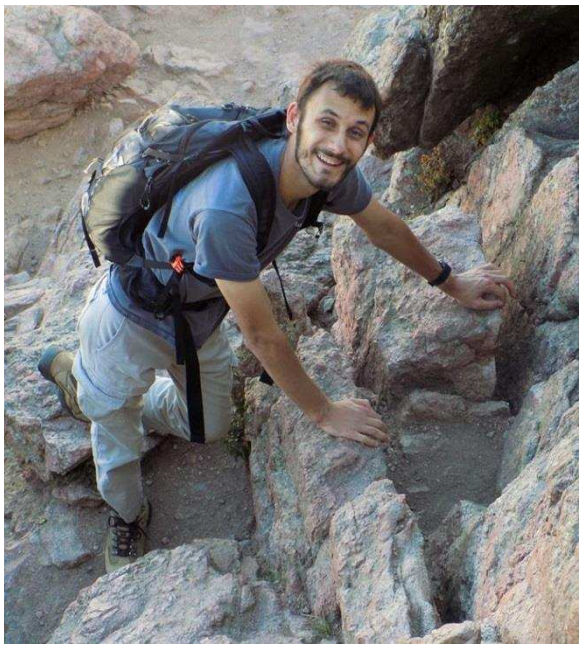
AUTOBIOGRAPHY

My name is Spencer Vore and I grew up in Centennial, Colorado. After my graduation from Heritage High School, I moved down to Atlanta, Georgia where I attended the Georgia Institute of Technology. As an undergraduate, I obtained a Bachelor of Science in Mechanical Engineering and graduated with highest honors. At Georgia Tech, I was also a member of the Honors Program and I worked as an undergraduate teaching assistant in the Math Department. In addition, I studied abroad in Metz, France at the Georgia Tech Lorraine satellite campus during my junior year where I picked up a little bit of basic French. During my summers as an undergraduate, I had two summer internships at BASF in Freeport, Texas and Eli Lilly and Company in Indianapolis, Indiana. I also spent one summer working as an undergraduate research assistant in the Georgia Tech School of Material Science and Engineering, where I prepared and tested samples for ballistic impact testing research.

After I graduated from Georgia Tech, I spent two years working for Freudenberg-NOK Sealing Technologies in a rotational development program called the Emerging Professionals Program (or EPP). In this program, I was moved to New Hampshire, Michigan, and Indiana where I worked in different factories and roles. The experience that I gained during this program with Freudenberg-NOK was targeted towards product engineering.

After spending two years at Freudenberg-NOK, I met my research advisor Dr. Thomas Bradley. He provided me with an opportunity to attend a fully funded Masters of Science program in Mechanical Engineering at Colorado State University and write this thesis. While I

was working on the research presented in this thesis at Colorado State University, I also had a summer internship at the National Renewable Energy Laboratory (NREL) in Golden, Colorado where I worked as a data analyst.



In my free time over the years, I have participated in activities ranging from fencing, hiking, rock climbing, swing dancing, and playing the flute in band. Having grown up in Colorado, I especially enjoy spending time outdoors and in the mountains. The picture of me on the right was taken in 2016 on top of Horsetooth Rock near Fort Collins, Colorado. I also enjoy traveling to new places, meeting new people, and learning about new cultures.

I hope you'll enjoy reading about the research that I've compiled into this thesis and I hope that it will be beneficial to your own research work or general knowledge.

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SECTION 1

INTRODUCTION

This research involved the development of a software toolset to enable the collection, processing, and analysis of large amounts of data from the vehicle controller area networks (CAN) of a fleet of plug-in hybrid electric vehicles. The data is processed using big-data concepts and software to answer various research questions about the real-world utility of these novel-limited production vehicles. Sample results, discussion, and recommendations to improve future data analysis are provided later in the document.

Before an in depth explanation of these research tasks and results is given, the first step is to define some of the basic technology and systems that are central to this study. The following introduction section introduces concepts such as Plug-in Hybrid Electric Vehicles (PHEV's), what specific vehicle platforms are being monitored for this study, CAN networks, data collection, and big data. Finally, a brief summary of the research workflow is presented at the end of this introduction in Subsections 1.6 and 1.7.

1.1 What Is Plug-In Hybrid Electric Vehicle Technology?

Plug-in Hybrid Electric Vehicle (PHEV) Technology is a rapidly growing automotive technology that expands on the concept of a traditional Hybrid Electric Vehicle (HEV) by allowing the driver to directly charge the hybrid vehicle battery [2, 3]. PHEV's use a small electric battery as the primary form of propulsion and then use a gasoline or diesel engine as a backup propulsion system when the battery gets low and more driving range is needed [2, 3, 4, and 5]. PHEV's can also be thought of as range extending vehicles, which use a less desirable

form of fuel to extend the range when the primary fuel runs out [2, 6]. Some well-known examples of PHEV vehicles that are currently on the market are the Chevy Volt, the Toyota Prius Plug-in Hybrid, BMW i8, and the Ford Fusion Energi [3, 7, 8, 9, and 10].

PHEV's typically have two different drive modes: a charge-depleting (CD) mode and a charge-sustaining (CS) mode [2, 11]. In the charge-depleting mode, the vehicle typically drains its battery until it reaches a threshold that is commonly around 25% battery state of charge, as in the Chevy Volt [10]. Once this threshold is reached, the vehicle transitions into a charge-sustaining mode where it operates in a traditional Hybrid Electric Vehicle (HEV) mode [12, 13]. In the HEV CS mode, the vehicle still uses battery power, but the battery is also recharged by HEV control strategies such as regenerative braking so the net energy loss out of the battery is approximately zero [13]. Hence the battery charge in charge-sustaining mode is "sustained." In the charge-depleting mode, there are typically different strategies for charge depletion [14]. Some vehicles such as the Chevy Volt [3, 10] or Via truck [3, 15] use a pure Electric-Vehicle (EV) charge depleting mode where the vehicle is solely propelled by the electric motor and the conventional engine mostly stays off. Other vehicles, such as the Odyne trucks in our study, use a blended charge-depleting mode [15]. In a blended charge-depleting mode, gasoline or diesel is still used when the vehicle charge depletes, but the battery is drained and the electric motor is used to reduce the fuel consumption [2, 14]. A blended charge-depleting mode is a good strategy when an electric motor cannot provide the raw torque and power to propel a heavy vehicle, so it makes sense to combine the electric motor torque with the torque from a conventional engine [14].

Below are some pictures of a 2013 Chevrolet ("Chevy") Volt PHEV that is plugged into an electric vehicle charging station. This vehicle is owned by Colorado State University

and I took these pictures myself in front of our Powerhouse Energy Campus building. The first photograph presented in Figure 1.1 shows the entire vehicle plugged into its charging station. The left photograph in Figure 1.2 shows a closer view of the electric vehicle charging station and the right photograph in the same figure shows a close up of the charging connector and port. Note that the Colorado State University Chevy Volt shown in these pictures was not involved with EPRI's data collection efforts and it is only show to provide a real-world sense of what a PHEV and an electric vehicle charging station are.

Figure 1.1 – Photograph of a 2013 Chevrolet Volt PHEV Connected to Its Charging Station

Figure 1.2 – Close up Photographs of an Electric Vehicle Charging Station and Connector

1.2 Information About the Specific Vehicle Platforms That Were Monitored By the Data Collection System for This Study

For the data analysis presented in this document, the EPRI Commercial Truck dataset was used [15]. This dataset was brought online in January 2015 and most of the data analysis discussed in this thesis covers data collected through July 2015. There are two different fleets of vehicles in this dataset. The first fleet consists of 119 medium-duty Odyne electric trucks and the second fleet consists of 177 light-duty Via electric trucks [15]. Later in this document, the results for these two fleets of vehicles are analyzed and presented separately.

For more details about EPRI's project to build and evaluate these Odyne and Via Trucks, see EPRI's corporate technical report entitled *Plug-In Hybrid Medium Duty Truck Demonstration and Evaluation* [15]. This EPRI report is a great resource for additional,

general information about the Odyne and Via truck models and the EPRI Commercial Truck dataset that used for this research. The EPRI report includes additional information about program management, program history, vehicle specifications, vehicle design, powertrain configurations, the data collection system, and vehicle manufacturing among other topics. The EPRI report also presents additional data analysis on their Commercial Truck dataset that was conducted at EPRI independently of the data analysis efforts here at CSU. The following two subsections (1.2.1 and 1.2.2) summarize some basic information about what the Odyne and Via vehicle platforms are, as these are custom, limited-release vehicles. The summary is mostly based on the more detailed information that is presented in EPRI's report [15].

1.2.1 Overview of the Odyne Vehicle System

The Odyne vehicle systems use a parallel powertrain configuration where both the electric motor and the diesel engine can provide power directly to the driveshaft [2, 3, 11, 13, 15, 16, and 17]. The hybrid system in the vehicle is simply added onto standard OEM drivetrains manufactured by International, Kenworth, Ford, Freightliner, and FCCC [15]. The Odyne system was determined to be what is called a "mild hybrid" [3, 16, 18, and 19] by examining its ratio of fuel to electric consumption and the relative size of its electric motor compared to its conventional engine [15, 20]. When a vehicle is classified as a mild hybrid, it means that the vehicle is primarily propelled by a conventional engine and it only uses a small electric motor to provide assistance when it improves driving efficiency [3, 16, 18, and 19]. Mild hybrids generally cannot propel themselves using only the electric motor. Note that although some works define a mild-hybrid car as having a 42 V electric motor [19] and the Odyne has a much higher voltage system [15, 20], the Odyne system can still be classified as a

mild hybrid since the Odyne system is a much larger truck application and is not a car. It is more important to consider the relative size of the electric motor to the conventional engine than just the absolute size of the electric motor in this situation.

The Odyne system also has three basic operational modes: drive mode, stationary mode, and charge mode [15]. The drive and charge modes are pretty self-explanatory: they correlate to when the vehicle is driving and charging. When the vehicle is operating in stationary mode, it is parked and uses electric power to operate hydraulic equipment, pneumatic equipment, external equipment, heating, and/or air conditioning. In addition to these drive modes, the Odyne vehicles are also programmed with either a mild or aggressive powertrain calibration [15]. When the vehicle is programmed with an aggressive calibration, it drains the battery energy more quickly when the vehicle is driving. The truck driver cannot change the calibration of the vehicle [15] so it is basically a preset parameter. Finally, it should be noted that the Odyne trucks were configured with two different battery sizes: a 14-kWh battery and a 28-kWh battery [15].

Below in Figure 1.3 is a graphic (originally presented in EPRI's report [15]) that contains photographs of the different Odyne body types along with a pie chart that shows the relative makeup of each body type in the entire Odyne fleet. Note that Odyne was manufactured with different body types for different purposes. When the Odyne data was analyzed, these different body types were not separated for the data analysis or the final results.

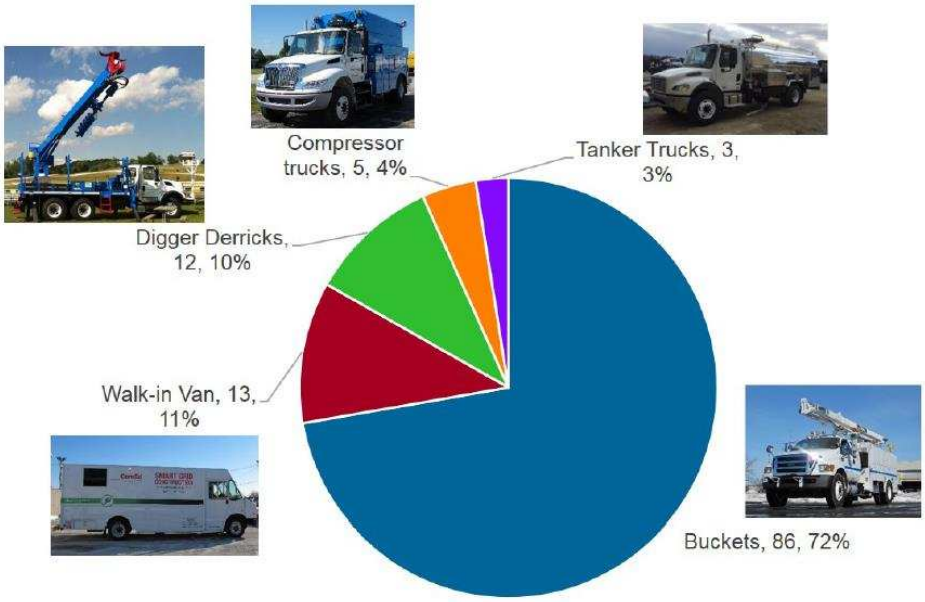

Figure 1.3 – Odyne Truck Models (from EPRI Report) [15]

An additional photograph of an Odyne truck in the digger configuration (originally from EPRI's report [15]) is shown below in Figure 1.4.

Figure 1.4 – Odyne Truck in Digger Derrick Configuration (from EPRI Report) [15]

1.2.2 Overview of the Via Vehicle System

Unlike Odyne, the Via platforms use a series powertrain configuration [3, 15]. In a series hybrid powertrain configuration, the electric motor provides all of the propulsion power that goes directly to the wheels and the conventional engine is only coupled to a generator which provides electric power for the battery pack and traction motor [2, 3, 15, 16, 21, and 22]. Also, unlike Odyne, the Via systems burn gasoline fuel instead of diesel fuel in their conventional engines [15]. The all-electric range of a Via hybrid is up to 47 miles [15]. Like Odyne, the Via hybrid system is an added system that can be installed onto a conventional truck platform, so Via is just a modified conventional truck. In this case, the trucks are manufactured by Chevrolet [15]. The Via system can also be built into a van configuration as well [15]. When the Via is driving in its charge-depleting mode, it will only use battery power for propulsion [15, 21, and 22]. The engine will only turn on in its charge-sustaining mode [15]. Since Via can drive in a pure Electric Vehicle (EV) mode due to its series powertrain configuration, it would be classified as a full-hybrid instead of a mild hybrid [3, 16].

Below in Figure 1.5 is a graphic (originally presented in EPRI's report [15]) that contains photographs of the different Via body types along with a pie chart that shows the relative makeup of each body type in the entire Via Fleet [15]. Note that Via was manufactured with different body types for different purposes. When Via data was analyzed, these different body types were not separated for the data analysis or the final results.

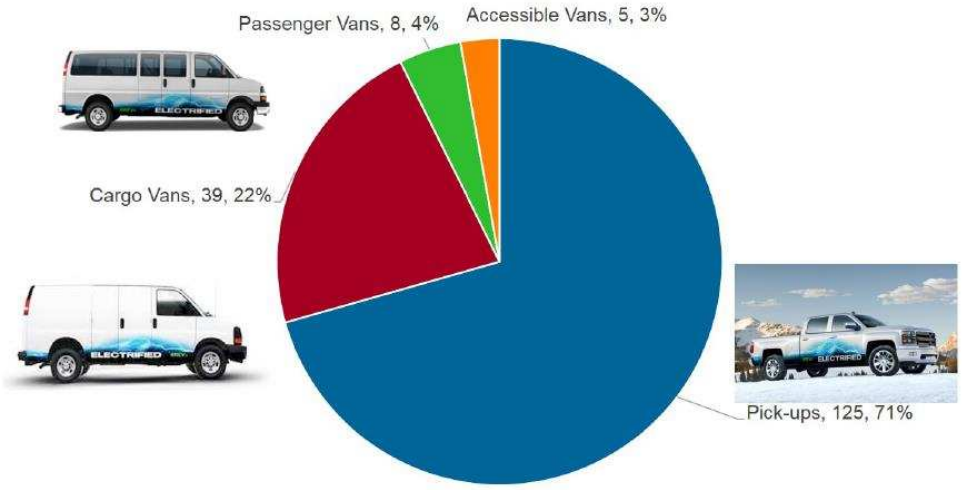

Figure 1.5 – Via Truck Models (from EPRI Report) [15]

An additional photograph of a Via pickup truck towing a boat (originally from EPRI's report [15]) is shown below in Figure 1.6.

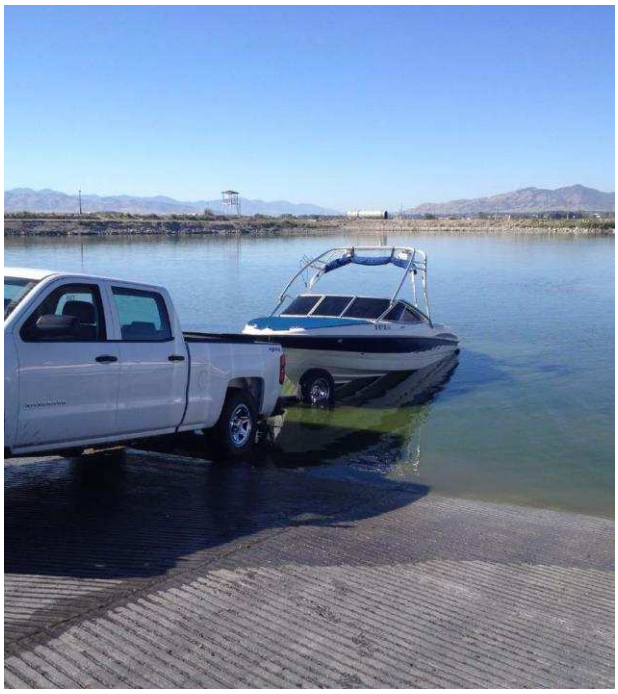

Figure 1.6 – Via Truck Towing a Boat (from EPRI Report) [15]

1.3 What Is the Onboard CAN-Communication Network on a Vehicle?

Most modern vehicles are equipped with a network of sensors and computers known as a CAN network [23, 24, and 25]. The CAN network monitors pretty much every function on the vehicle, ranging from vehicle speed, to engine temperature, to whether the lights are turned on. In addition, these on board computers are responsible for controlling the vehicle and transmitting driver requests to the appropriate mechanisms on the vehicle. A mechanic can also connect to this system to diagnose problems with the vehicle using the OBD-II port. Many of the CAN signals on a vehicle are documented in published engineering standards [23, 24] but others are proprietary and specific to individual vehicle models or manufacturers.

1.4 Information About the Data Collection System Installed Onboard the Vehicles

To collect vehicle tracking data from these vehicles for this study, the Electric Power Research Institute (EPRI) connected GSM / CDMA transmitters into the OBD-II ports to collect and decode the CAN signals [15]. This information was then sent to a central database and Colorado State University was given access to this central database through its contracts with EPRI.

Most of the CAN signals were recorded every second while the vehicle was in operation, so the data-sampling frequency was very high. High-rate data sampling has many advantages. For example, it provides the capability to investigate short-term events and improves the overall accuracy of the calculations. However, the high-data sampling frequency also presents challenges in terms of managing and processing large amounts of data. In total, about 160GB of CSV data were downloaded from the central Amazon Redshift database and processed for this analysis work. A MATLAB script running on a single core took multiple

days to fully analyze the dataset. In addition, not every CAN-communication bus signal was utilized for this study and the data that was downloaded from the full database using SQL is just a subset of the total available fleet data.

Near the very end of this project, a new version of the Odyne and Via datasets became available. This new version of the dataset was available for download from Amazon Web Services (AWS) using its command line interface and CSU was told that the new data had additional pre-cleaning. However, due to time constraints, this new data was only utilized for a small portion of the data analysis presented in this thesis and the old database that was downloaded using SQL was used for most of the data analysis presented in this work.

Due to privacy considerations based on the detailed information contained in the database, this dataset is not publically available and is considered protected information. EPRI is solely responsible for granting and denying access to this dataset. Please contact EPRI for questions or inquiries regarding this dataset, or to request access. Mark Kosowski was our main point of contact at EPRI for the EPRI Commercial Truck dataset [15].

1.5 Overview of "Big Data" as a Concept Beyond Fleet Data.

Recently, as computer networking has enabled data to be collected from an ever larger number of sensors, users, and sources, "Big Data" has become a rapidly growing field [26, 27, 28, and 29]. As computer, electronic, and networking technology improves and becomes less expensive, it is increasingly easier to collect vast amounts of data that are orders of magnitude larger than anything that has ever been collected before. The concept of analyzing huge datasets can be applied to numerous and diverse applications, such as improving airline estimated time of arrival predictions [28], online advertising [28], atmospheric science [29],

supply chain management [27], health care [27], detecting influenza epidemics by using search engine query data [30], and analyzing particle accelerator data from the Large Hadron Collider [31].

However, big data presents many new challenges as well [26, 28, 29, and 32]. For example, when compared to traditional data analytics and statistics, big data generally has a record count that is orders of magnitude larger (aka. volume) [28, 29]. It also can have a high data creation rate (aka velocity) and can have a large variety of different signals and formats (aka variety) [28, 29]. In addition, these very large datasets often contain numerous errors and bad records that must be either filtered out or dealt with in some other way. This can create immense data computation and processing challenges that need to be overcome. Traditional methods of data analysis such as using Microsoft Excel soon become obsolete. Big data creates a paradox: we can know so much about so many different variables in our system that we no longer know what the information represents as a whole. Without new tools and methods for big data analysis, big data is useless for making decisions.

Some tools and frameworks that are currently popular for managing big data include Hadoop Distributed File System (HDFS) and MapReduce [29, 33], Google File System [29], Tableau [31], NoSQL [31], Amazon Web Services [31], Storm [31], and many more. Using tools designed specifically for large datasets, actionable conclusions can again be derived from these truly massive datasets. Depending on the situation, custom software solutions can also be developed. In addition, some big data problems rely on machine learning algorithms and artificial intelligence to make sense out of the large variety of data [31].

Vehicle fleet-tracking data is considered to be a unique subset of big data analysis within the full scope of big data problems outlined above. For much of the work in this study,

a custom MATLAB framework was used, as well as some Hadoop MapReduce. Since our team mostly consists of mechanical engineers with experience in automotive technology, machine learning techniques were not used. Instead, we developed our methods and calculations by using our knowledge and experience with hybrid and electric vehicle technology. Having subject area expertise in the application from where big data is being collected is a huge advantage that can make up for some lack of computer science and programming experience.

1.6 Research Tasks

Based on this background understanding of the field and the available data, the research program described in this thesis seeks to develop big-data software tools and techniques to collect, process, and analyze data from fleets of Odyne and Via PHEVs operating in the real-world. The research tasks that this project seeks to develop are:

Task 1 - The construction of a MATLAB data analysis software framework that can meet the goals of preparing the under-structured data output from the vehicles for research-level analysis. Details are provided in Section 2.

Task 2 - The development of a set of research questions and corresponding recommendations for data collection, processing, and analysis that can inform the ongoing EPRI data collection practices and future research. Details are provided in Section 3.

Task 3 - The development, testing, and validation of a method for processing the raw data output from the vehicles into "event-based" objects so as to characterize vehicle events such as charging, driving, etc. Details are provided in Section 4.

Task 4 - Based on these outcomes, this work will answer a subset of the research questions proposed in Task 2 so as to demonstrate the utility of the proposed data management and decision support systems. Results and details are provided in Sections 4 and 5.

Below in Figure 1.7 is a simple diagram that shows the workflow of the research project, as well as the scope of the work performed here at CSU. Most of the data collection and storage work was done outside of CSU and was managed by EPRI.

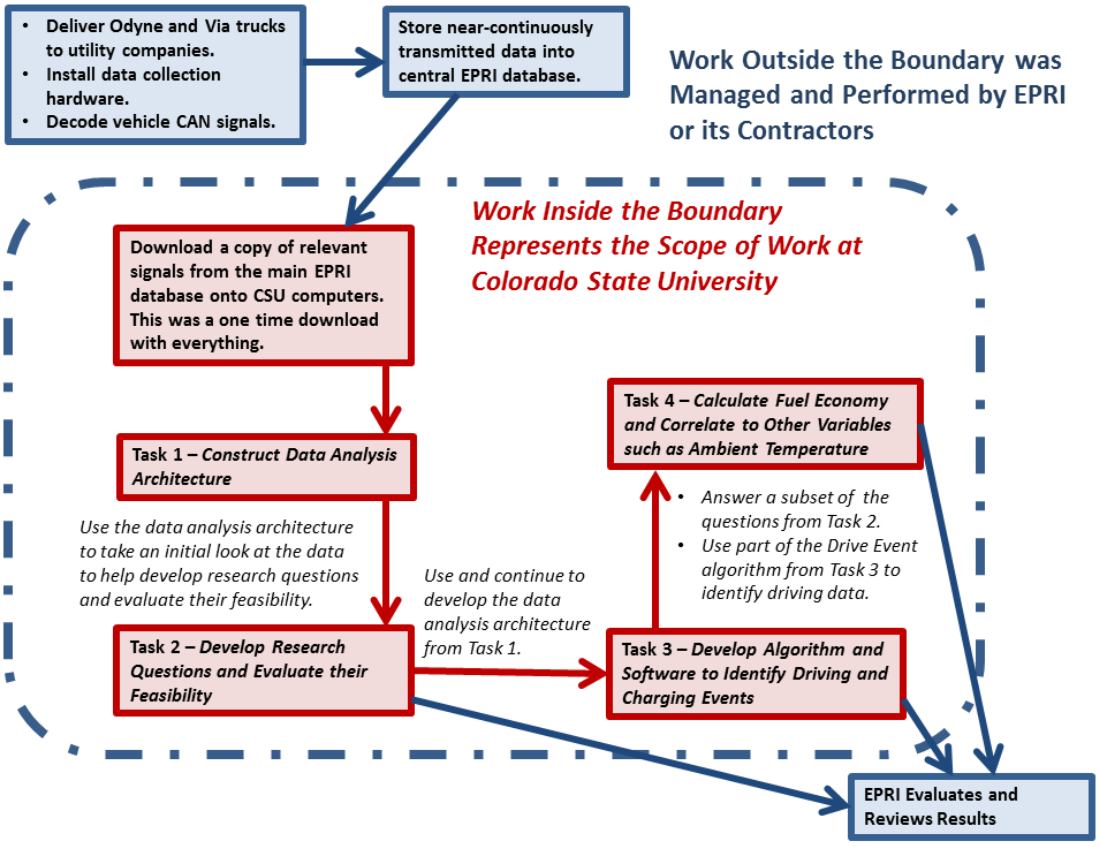

Figure 1.7 – High-Level Project Workflow and Project Scope

1.7 Summary of This Document

This work discusses methodologies for analyzing this vehicle fleet-tracking data after data is collected and presents results derived from the EPRI Commercial Truck datasets.

Section 2 discusses a MATLAB framework that was initially constructed to manage data processing and analysis and which served as a foundation for future work in the later sections of this thesis. This section corresponds to Task 1 which was defined in the previous Subsection 1.6.

Section 3 provides an overview of some research questions that were reviewed to determine if they were feasible to answer and a high-level analysis to determine what data and analysis methodologies might be needed to answer the question. This provided a basis to determine what research questions were possible to answer and later sections of this thesis discuss some of these results. This section corresponds to Task 2 which was defined in the previous Subsection 1.6.

Section 4 provides a description of a drive and charge event identification algorithm that summarizes second-by-second sensor data into a list of higher-level drive and charge "events." This work was also presented at the Electric Vehicle Symposium 29 (EVS29) in Montreal, Quebec in June 2016 [1]. In this study, a drive event is considered to be a single trip taken by a driver, starting when the vehicle began moving and ending when it stopped moving. Similarly, a charge event is considered to be the time starting when the vehicle was plugged in and power was being transmitted to the vehicle and ending when the power transmission terminated. After the data is summarized into these "event-based" objects, it is much easier to analyze and produce meaningful results for a significant number of research questions. Sample results created using the summarized data are also presented. This section corresponds to Task

3 which was defined in the previous Subsection 1.6. Some of the presented results also correspond to Task 4 in the same subsection.

Section 5 discusses an algorithm that correlates vehicle fuel economy to other variables such as ambient temperature. The drive event identification algorithm presented in Section 4 is used as a component in the algorithm presented in Section 5. Sample results from this algorithm are also presented. This section corresponds to Task 4 which was defined in the previous Subsection 1.6.

Section 6 provides a high-level discussion about the real-world impacts of fleet-level data collection and analysis. This discussion covers topics such as why fleet data analysis methodologies need to be better defined, how real-world fleet data can complement standard tests such as EPA drive cycles, and how fleet data analysis can influence policy related to electric vehicles. In addition, the assumptions and potential pitfalls behind our data analysis project are discussed. Examples to support these claims are provided.

Section 7 outlines future work that can be taken to answer some of the additional questions raised by this thesis and to address some of the assumptions and pitfalls discussed in Section 6. The proposed future work should help further validate and refine the techniques proposed by this thesis and generate additional results.

Finally, conclusions are presented at the end of this document.

In addition, after the bibliography, there is an Appendix that provides some additional, general discussion that might be useful to anyone who is trying to collect and analyze data from fleets of vehicles. Topics discussed here include data security, privacy, problems encountered working with CAN network data, and considerations for choosing the right software and/or programming language for a data analysis framework. The purpose of the

Appendix is not to provide scientific conclusions or solutions, but instead to just provide some general considerations and advice that should be accounted for when implementing this type of vehicle data collection and analysis project.

SECTION 2

DEVELOPMENT OF MATLAB DATA MANAGEMENT FRAMEWORK

2.1 Overview of the MATLAB Data Management Framework Software

Before any assessment of the dataset or analysis could be performed, the first obstacle was determining how to manage the large quantity of data. For example, the Odyne Medium-Duty Truck dataset at CSU had 140 GB's of data and the Via Light-Duty Truck dataset at CSU had 17 GB's of data. In addition, the Odyne and Via datasets at CSU were not complete datasets and only contained a subset of the total signals that were available in EPRI's main database. In addition, these datasets are stored in a collection of multiple CSV files and the data files contained errors and formatting problems that required robustness in the data analysis tools. CSU was also contracted by EPRI to analyze some other datasets collected from other vehicle platforms, but due to confidentiality agreements those unfortunately cannot be discussed in this document. However, the software and methods described in this section are just tools that can in theory be applied to any vehicle fleet-tracking dataset. There were slightly different versions of this software designed for the specifics of each dataset, but the fundamentals were basically the same.

My first project was to figure out how to manage these datasets in MATLAB. The solution was to create a data analysis framework that separated the data analysis code that might be later added to generate scientific results from the data management code. Tasks that can be managed by the data analysis framework include:

1) Automating the loading process of hundreds of individual CSV files for analysis.

2) Parsing the data file format to extract and reformat the raw signals into a more user friendly format.
3) Converting timestamps into serial date numbers, which are easier to add, subtract, and plot.
4) Splitting very large CSV files up into multiple pieces, so as to not overload the available RAM on a standard desktop machine. For some reason, when MATLAB loads a data file, that data takes up significantly more RAM than disk usage. For example, a 113 MB .mat file containing vehicle data (converted from a CSV file that was 971 MB in size), increased the RAM usage of the computer by 7.8 GB's. I do not have enough familiarity with MATLAB to understand why this large increase in memory occurs. Fortunately, only a few raw data CSV files completely overloaded all 16 GB's of the available RAM on the computer and needed to be split into multiple chunks.
5) Removing formatting errors in files that could crash the data management or analysis software.
6) Saving intermediate data into a .mat format that is more convenient to data analysis work.
7) Tracking custom error conditions and referencing them to a particular data file. These error conditions include improperly formatted data, or missing data.

This software was developed through multiple iterations. The first version of the software was developed for other vehicle tracking projects that cannot be discussed here due to confidentiality and contract reasons. Then, the software was reconfigured and modified again

to run on both the Odyne and Via Truck data from EPRI. Numerous improvements were implemented during each of the software iterations. This thesis only focuses on the final version of the software that I developed. For the Electric Vehicle Symposium 29 (EVS29) conference paper, Zachary Wilkins further modified the framework described in this document to better suit his needs, but his work on the data management framework will not be heavily described in this document. In addition, much of this framework was rewritten by Mike Reid for the analysis work presented in Section 5 and Subsection 5.2 and it served as a foundation to develop new versions of the analysis software.

There are two main components in this framework that run as separate scripts. The first is a data extraction and parsing framework which runs through the script titled *Extract_all_Truck_data_v1.m.* This first component was responsible for parsing the raw CSV data files, reformatting the data, removing any obvious formatting errors, and then resaving the data into a .mat file format. By resaving the data, subsequent data analysis would not have to rerun this initial data parsing and validation step. All data analysis can be run directly out of the .mat files.

The second main component of the framework is where scientific data analysis code can be added later, which runs through the script titled *Analyze_all_truck_data_v1.m*. The raw code is mostly just a framework that additional analysis code can be added into. This empty framework is responsible for keeping track of all the data files to be processed and then passing the file names to a sub-function where each data file is loaded and processed independently. The framework also includes a custom error tracking system, where the future data analysis code can flag custom error conditions when it is processing certain data files. These error codes are then summarized for all data files at the end of the script run. Finally, the framework

can reduce each data file into a single Excel spreadsheet row, so information such as fuel consumption, total distance traveled, etc. can be compiled by vehicle. All the spreadsheet rows are then combined into a single Excel spreadsheet. The idea was that fleet-level analysis could be performed on this output spreadsheet using Excel and no additional MATLAB development would be needed to combine vehicle results into fleet results.

The below flowchart summarizes the data processing flow inside of this framework as the data moves through the data extraction and analysis software modules:

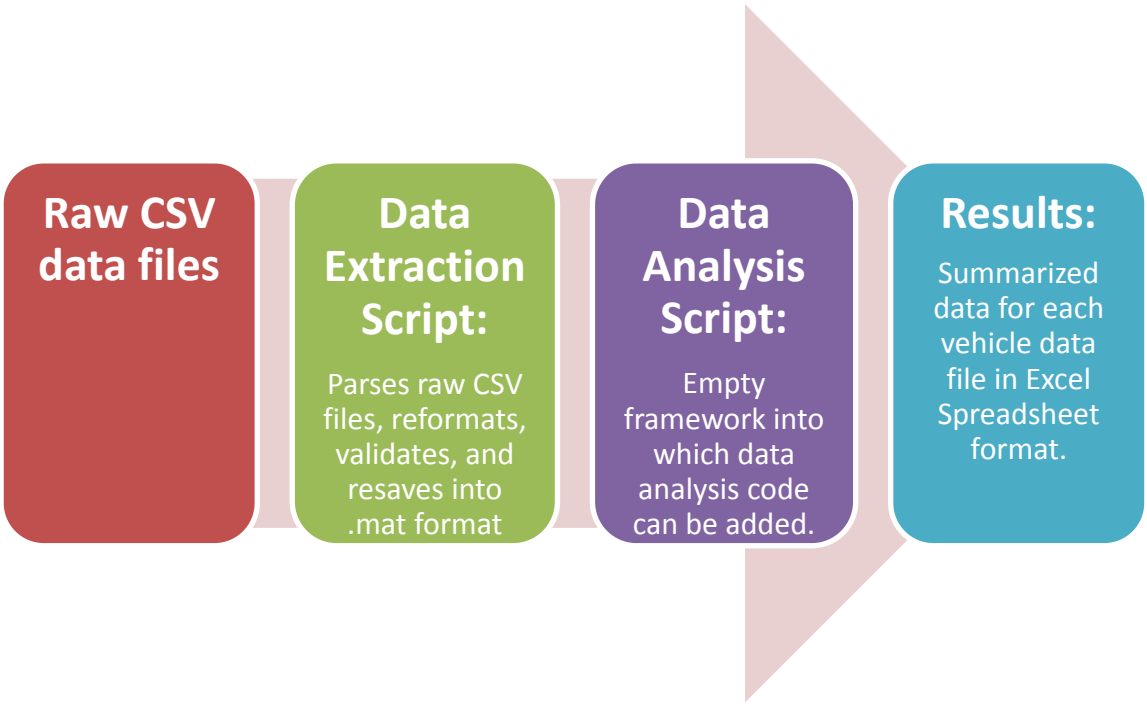

Figure 2.1 – High-Level Data Processing Flow between Modules of the MATLAB Data Management Framework

2.2 Details of the Data Extraction and Parsing Component

This section describes in more detail how the data extraction script works for the EPRI Commercial Truck data.

The *Extract_all_Truck_data_v1.m* data extraction script is a preprocessing step for the *Analyze_all_truck_data_v1.m* script, which is explained next in Subsection 2.3. The goal of the *Extract_all_Truck_data_v1.m* script is to perform data reformatting, data validation, and save the data into a .mat format that is faster to load and process during data analysis. This way, when the data analysis needs to be run multiple times for development and debugging, all of this up front work will not need to be rerun.

Data validation is built into the software, to identify any corrupt data. For example, the software checks that each line of CSV data has the proper number of delimiters, each file has a proper header, and after the data is parsed from the CSV file it again checks the size of the data to ensure that all of the data was properly imported. If there are corrupt lines of data, the process will attempt to remove these lines so the non-corrupt lines can still be used. When corrupt data is encountered, an error code will be generated, a summary of errors will be displayed in the command window when the script completes, and the command window output can be continuously appended into a text file (if runlog is activated).

The code is structured into two main levels. The highest level script tracks all of the data files to be processed and collects error codes, while the *epri_truck_data_file_extract_fcn_v1.m* sub-function, which is called from the high-level script, processes individual data files. Multiple .mat data files may be created for a single CSV file if the data size is too large so available RAM is not overloaded. This sub-function also contains data validation tools that will prevent the loading of corrupt CSV data. In addition, if the function header is commented out and the input variables are defined explicitly in the function (there is a commented out section of code just for this), it can be run as a script for testing purposes.

All of the parameters needed to adjust the performance of the *Extract_all_Truck_data_v1.m* are in a *Controlling Variables* section near the top of the script. Comments provide additional explanation of these variables. For example, these variables define which directories data should be read from and saved to, and define switches that can turn on and off certain script functions.

```
%% CONTROLLING VARIABLES - Use the controlling values to adjust the performance
of the script.
% This section is used to initialize the script, point it towards the
% appropriate file directories, etc.
%
% Be sure to save this script after changes if it will be launched by
% another script.

% SET CURRENT DIRECTORY
 cd('T:\projects\EPRI2014\MATLAB\Odyne Data and Analysis') % Windows
% cd('/net/projects/data/projects/EPRI2014/MATLAB') ;% Linux Server


% RUN PROFILES.
% Each run profile is a branch of an if statement, and the control_profile
% variable controls with branch is run to initialize the script.
% This allows the user to quickly switch between different commonly used run
settings.
% Additional elseif statements can be added to create new run profiles if
% needed.
%
% Values:
% 1 - Actual Data (Test)
% 2 - Data Validation Test
 control_profile = 2 ;




% --------------------------------------------------------------------------
% PROFILE 1 - ACTUAL DATA VIA TEST
if control_profile == 1;

% DIRECTORY TO LOAD - CSV DATA
 control_filedir_load = 'T:\projects\EPRI2014\MATLAB\Odyne Data and
Analysis\Data\CSV\Via_Join_Test/' ; % Test Data
 % Location of files to be extracted relative to CD.  Be sure to include \ at end
of string.

% DIRECTORY TO SAVE EXTRACTED MAT DATA
 control_filedir_save = 'T:\projects\EPRI2014\MATLAB\Odyne Data and
Analysis\Data\MAT\Via_Join_Test_MAT/' ; % Test Data
 % Location of where to save processed .mat file relative to CD.  Be sure to
include \ at end of string.

% DO YOU WANT TO CREATE A RUNLOG FOR TROUBLESHOOTING?
% This is recommended when large amounts of data are being processed to
```

```
% help troubleshoot a system crash, or verify the accuracy of results.  It also
provides documentation of the
% conversion process.
 control_create_runlog = 1 ;
 % 0 - do not create a runlog when script executes.
 % 1 - save runlog in designated location.
 control_runlog_nameandloc = [control_filedir_save
'Extract_all_Truck_data_v1_runlog' ] ; % Test Data

 % Specify runlog file name and location in relation to the CD as a
 % text string.  Note that script start time and .txt will be appended
 % onto the end of the runlog file name specified.

% DEFINE MAX NUMBER OF DATA LINES PER .MAT FILE
 control_max_number_of_datalines = 1250000 ;
 % This value defines the maximum number of data lines that can be loaded and
saved
 % into a .mat file at a time.  This is to prevent RAM from being maxed
 % out and crashing the machine when very large data files need to be
 % processed, so they can be processed on a regular computer.  CSV files
 % with more data lines than the maximum will automatically be split up
 % into multiple .mat files.




% ------------------------------------------------------------------------
% PROFILE 2 - DATA VALIDATION TEST
elseif control_profile == 2;


% DIRECTORY TO LOAD - CSV DATA
```

Figure 2.2 - Controlling Variables Section of Code

The first section of MATLAB code (Figure 2.2 above) shows the controlling variables section. Since the user may have multiple configurations that they frequently run, such as a configuration for testing and a configuration for actual data analysis, different profiles can be created to save these settings so they do not need to be constantly adjusted. To create a new profile, copy all of the variables from an existing profile and put the copy into a new branch of the if-else statement. The *control_profile* variable is just a number that tells the script which section of the if-statement to execute for a given configuration. The goal of this system is to make it very easy to switch between different settings to reduce setup errors.

Figure 2.2 above also shows the settings within one of these run profiles, below the section of the code where the configuration is defined. Some of these variables are switches that turn different script functions on or off. For example, if the variable *control_create_runlog = 1*, a runlog of the command window output will be created in the designated folder location with the designated file name. However, the runlog will not be created if *control_create_runlog = 0*.

In this section, be sure to specify which directory contains all the raw CSV data that needs to be converted and what directory converted .mat data should be saved into. These can be the same folder, or different folders. Please note that file paths can be relative to the current directory (CD), or can be defined as absolute file paths. These file paths can then be later used to specify the location of other items, such as the runlog save location, to prevent the file path from being specified multiple times. This again, will help reduce setup errors and make configuration more convenient.

There is also an option that controls the maximum number of data lines that can be saved into a .mat file. This is a memory management control. Some CSV files may contain enough data to overload the available RAM on a standard desktop machine, or others have too much data to be saved into a single regular .mat file. Any CSV file with more than the maximum number of data lines specified will be split into multiple .mat files.

Note that all of the variable names in the controlling variable section start with the prefix *control_* so they are not confused with other variables defined later in the script. Once the controlling variables are adjusted to the user's preferences, they can run the script and wait for results. This process can take quite a long time, depending on the amount of data. It is

recommended to start running the process overnight, and even then it still may not be finished by the next morning.

The sub-function that converts individual CSV files to .mat data has the following format (shown below in Figure 2.3):

```
[errorcode critical_fileerror] =
epri_truck_data_file_extract_fcn_v1(filedir_load,
       filename_load, filedir_save, filename_save, max_number_of_datalines)
```

Figure 2.3 - Format of the Data Extraction Sub-Function for Individual CSV Files

Function output is optional and only indicates if an error was encountered. While the function is running, information will be printed into the command window as well so it may not be necessary to collect the error code output. The *errorcode* output variable contains numbers that correspond to specific error conditions. This can be a single number, or an array of numbers for multiple error conditions. Note that an *errorcode* of 0 indicates that no errors occurred. The *critical_fileerror* output variable will always be a single value that indicates the severity of all the error conditions encountered and it helps define what actions should be taken by the higher level script. A *critical_fileerror* of 0 indicates that the *errorcode* is more of an advisory to the user and no automated response is needed. A *critical_fileerror* of 1 indicates that some of the .mat data files corresponding to the CSV file may be deleted due to corrupt data. A *critical_fileerror* of 2 indicates that no .mat data should be saved for the vehicle and any .mat data saved previously should be deleted (note, the functionality to delete data files may not be in the extract data script for the medium duty truck data as *critical_fileerror* of 2 is not used in this script). *critical_fileerror* = 2 is the most severe.

Additional error codes can be added into the *epri_truck_data_file_extract_fcn_v1* function if the software needs further development and compiled in the higher level *Extract_all_Truck_data_v1.m* script. The process to add new error conditions is the same as the process used in the analyze data script, so read Subsection 2.3 which is next about the analyze data script for more details.

2.3 Details of the Data Analysis Framework Component

After the data is transferred into .mat files by the data extraction script described in the previous Subsection 2.2, the next step is to analyze the data. This Subsection describes a framework that loads and manages the .mat files, and tracks error codes, into which additional data analysis code can be easily added. After loading these .mat files, the *Analyze_all_truck_data_v1.m* script will compile results from each individual .mat file into an Excel spreadsheet where fleet summary statistics can be compiled. A process to report error codes is also built into the script, so data files that have corrupt data, or do not process correctly, can be identified. Overall, this script can load and keep track of multiple data files, so fleet wide analysis can be performed.

The structure of the data analysis script is similar to the data extraction script, as the highest level of the script tracks and manages all of the data files and then a sub-function named *epri_truck_data_file_analyze_fcn_v1.m* loads each individual file and performs the analysis on the data within it. Much of the code from the data extraction script was copied to create the data analysis script.

The highest level *Analyze_all_truck_data_v1.m* script loads multiple .mat vehicle files in a directory for analysis. The script will compile a summary of the analysis output for each

vehicle into an Excel Spreadsheet. Results from the data analysis can also be saved into a .mat file, where the results are stored into a cell array that mimics the spreadsheet format. This script is a framework that future data analysis can be added into, although some simple sample data analysis, such as a count of the number of data points in the file, is included in the empty framework to demonstrate how the script works.

The *epri_truck_data_file_analyze_fcn_v1.m* sub-function analyses data in a single .mat vehicle file and outputs the results. Additional analysis code can be added into the body of this function in the future. The function is automatically invoked from the *Analyze_all_truck_data_v1.m* script, but it can also be run through the command window to analyze a single data file. In addition, if the function header is commented out and the input variables are defined explicitly in the function (there is a commented out section of code just for this), the function can be run as a script for testing purposes.

2.3.1 Instructions for Running the Data Analysis Framework

All of the parameters needed to adjust the performance of the *Analyze_all_truck_data_v1.m* script are in a *Controlling Variables* section near the top of the script. Comments provide additional explanation of these variables. This controlling variables section is shown below (in Figure 2.4).

```
%% CONTROLLING VARIABLES - Use the controlling values to adjust the performance
of the script.
% This section is used to initialize the script, point it towards the
% appropriate file directories, etc.
%
% Be sure to save this script after changes if it will be launched by
% another script.


% SET CURRENT DIRECTORY
 cd('T:\projects\EPRI2014\MATLAB\Odyne Data and Analysis') % Windows
% cd('/net/projects/data/projects/EPRI2014/MATLAB') % Linux Server


% RUN PROFILES.
% Each run profile is a branch of an if statement, and the control_profile
% variable controls with branch is run to initialize the script.
% This allows the user to quickly switch between different commonly used run
settings.
% Additional elseif statements can be added to create new run profiles if
% needed.
%
% Values:
% 1 - Data Validation Test
% 2 - Actual Data Odyne
% 3 - Actual Data Via
 control_profile = 2 ;




% --------------------------------------------------------------------------
% PROFILE 1 - TEST DATA
if control_profile == 1;


% DIRECTORY TO LOAD PREFERENCES - MAT DATA
 control_filedir_load = 'T:\projects\EPRI2014\MATLAB\Odyne Data and
Analysis\Data\MAT\Data_Validation_Test_MAT\' ; % Test folder location % Location
of .mat files to be analyzed relative to CD.  Be sure to include \ at end of
string.

% DIRECTORY TO SAVE ANALYSIS RESULTS
 control_results_save = 'T:\projects\EPRI2014\MATLAB\Odyne Data and
Analysis\Data\Analysis_Results\Data_Validation_Test_Results\' ;
 % Location of directory where all data analysis results will be saved.


% DO YOU WANT TO CREATE A RUNLOG FOR TROUBLESHOOTING?
% This is recommended when large amounts of data are being processed to
% help troubleshoot a system crash, or verify the accuracy of results.  It also
provides documentation of the
% conversion process.
 control_create_runlog = 1 ;
 % 0 - do not create a runlog when script executes.
 % 1 - save runlog in designated location.
 control_runlog_nameandloc = [control_results_save
'Analyze_all_truck_data_v1_runlog - Test' ] ; % Test data
 % Specify runlog file name and location in relation to the CD as a
 % text string.  Note that script start time and .txt will be appended
 % onto the end of the runlog file name specified.
```

```
% DO YOU WANT TO COMPILE A LIST OF ALL VEHICLES AND THEIR RESULTS INTO AN
% EXCEL SPREADSHEET?
 control_create_spreadsheet = 1 ;
 % 0 - do not create an excel spreadsheet that summarizes individual
 % vehicle results at the end of the script
 % 1 - Compile a summary of vehicle results into a spreadsheet at
 % the end of the script.
 control_nameandloc_create_spreadsheet = [control_results_save
'Analyze_all_truck_data_v1_spreadsheet_result_summary - test' ] ; % Test data
 % Specify spreadsheet name and location in relation to the CD as a
 % text string.  Note that .xls will be automatically included on the
 % end of the file name and does not need to be included in the text
 % string.

 % NOTE: Existing summary spreadsheets can be overwritten, but be sure
 % the summary spreadsheet is closed before running this script.


% DO YOU WANT TO USE A EXCEL VIN LIST SPREADSHEET TO MANUALLY FILTER OUT
% VEHICLE FILES FROM THE DATA ANALYSIS?
% This spreadsheet is a list of all VIN numbers, and it can be used to
% check which vin numbers should not be processed with an 'x'.

% Note: First column of the spreadsheet should contain a column that has
% either values of "x" or are blank.  The second column should contain
% vehicle vin numbers.  VIN numbers with X will be skipped during data analysis.
% Any additional columns will be ignored by this matlab script, but can be
% included if the information is helpful in the spreadsheet.
% "x" is not case sensitive and can have leading or trailing spaces.  This
% data should start on the second row of the spreadsheet.  It will be
% assumed that the first row is a header.

 control_load_vinlist_spreadsheet = 0 ;
 % 1 - Load a spreadsheet containing a list of vin numbers.  VIN
 % numbers marked with "x" will be excluded from the analysis.
 % 0 -Do not load a spreadsheet containing a list of vin numbers.

 control_vinlist_spreadsheet_nameandloc = [ control_filedir_load 'List_of_trucks-
test.xlsx' ] ; % Test Data
 % Specify the name and location relative to the CD where the
 % spreadsheet containing a list of VIN numbers is located.  Be sure
 % to include .xls or .xlsx at the end of the spreadsheet name.


% DO YOU WANT TO AUTOMATICALLY SAVE DATA ANALYSIS RESULTS INTO A .MAT FILE?

 control_save_results_as_mat = 1 ;
 % 1 - Save final workspace as .mat file after data analysis completes.
 % 0 - Do not save final workspace as .mat file.

 control_matresults_nameandloc = [control_results_save
'Analyze_all_truck_data_v1_mat_datafile.mat' ] ; %Test Data
 % filepath and filename relative to the CD where the .mat file of results should
be
 % saved.  Variable should be string.  Be sure to include .mat at the end of the
 % string.

% DO YOU WANT TO CREATE PLOTS AND FIGURES DURING THE DATA ANALYSIS PROCESS?

 control_save_figs = 0 ;
 % 1 - Save figures for each vehicle file in designated location.
 % 0 - Do not save any figures from data analysis.
 control_fig_save_loc = [control_results_save 'Figs\' ] ; % Test Data
```

```
 % filepath relative to CD where .fig files genereated in analysis
 % should be saved.  Variable should be a string.  Be sure to include
 % a \ at the end of the string.




% ------------------------------------------------------------------------
% PROFILE 2 - FULL DATA SET FOR ODYNE
elseif control_profile == 2;


% DIRECTORY TO LOAD PREFERENCES - MAT DATA
```

Figure 2.4 – Run Profile Settings in the Controlling Variables Section of Code

The first section of MATLAB code (in Figure 2.4 above) shows the control profile section. Since the user may have multiple configurations that they frequently run, such as a configuration for testing and a configuration for the full data analysis, different profiles can be created to save these settings so they do not need to be constantly adjusted. To create a new profile, copy all of the variables from an existing profile and put the copy into a new branch of the if-else statement. The *control_profile* variable is just a number that tells the script which section of the if-statement to execute for a given configuration. The goal of this system is to make it very easy to switch between different settings to reduce setup errors.

Figure 2.4 above also shows the settings within one of these run profiles. Some of these variables are switches that turn different script functions on or off. For example, if the variable *control_create_runlog = 1*, a runlog of the command window output will be created in the designated folder location with the designated file name. However, the runlog will not be created if *control_create_runlog = 0*.

In this section, be sure to specify which directory contains the .mat data files that need to be converted and where the final analysis results should be saved. Please note that file paths can be relative to the current directory (CD), or can be defined as absolute file paths. These file paths can then be later used to specify the location of other items such as the runlog save

location, spreadsheet result save location, and figure save location. By concatenating these general-high level file paths to create lower level folder structures, this prevents the file path from being typed by the user multiple times to reduce setup errors and make configuration more convenient. Basically, the setup is similar to the data extraction function, but with more options.

A major difference between this script and the extract all data script is that spreadsheets can be imported and exported. If *control_create_spreadsheet* = 1, all of the data analysis results will be exported into an Excel spreadsheet and saved in the designated location. The data analysis results for each vehicle are listed in the spreadsheet. Note that cell dimensions and formatting may need to be adjusted within the Excel interface after the spreadsheet is exported.

If there are multiple .mat files for a single vehicle file, there will be multiple rows of data output for that vehicle. The easiest way to combine results into a table that shows the cumulative results for a single vehicle on one line is to use a pivot table in Excel. I did not want to spend weeks programming MATLAB to do this when the capability was already built into Excel.

If *control_load_vinlist_spreadsheet* = 1, a control spreadsheet will be imported to help manually filter out individual vehicles. In the control spreadsheet, VIN numbers with an 'X' marked next to them will not be analyzed. The X's should be in the first column of the spreadsheet and the VIN numbers should be in the 2nd column of the spreadsheet. Any other columns are extra information and will be ignored by the *Analyze_all_truck_data_v1.m* script.

Note that 'X' is not case sensitive and can have leading and trailing blank spaces. It will also be assumed that the first row of the spreadsheet is a header and VIN numbers should

start on the second row. Be sure that the VIN list spreadsheet is formatted exactly as specified. Also note that a warning will be produced if the VIN number in the spreadsheet does not match the VIN number in the vehicle .mat file. Each vehicle data file should contain a VIN number before the first underscore (_) in the file name in this implementation of the framework.

Another option that can be selected is to automatically save the final workspace as a .mat file when the script completes. This offers an alternative format from which vehicle summary information can be analyzed and provides a data backup in case an Excel spreadsheet cannot be exported. If this option is turned on, the name and location of where the .mat file should be saved needs to be specified under controlling variables.

Finally, the last option allows custom figures and charts to be saved for each .mat file. The data analyst is responsible for programming the charts they want into the MATLAB data analysis framework, so this feature just creates an easy framework that can be turned on to manage these graphs. These can help the user visualize the data for individual vehicle files after a data analysis run and can also help spot problems in the dataset. However, a very large number of graphs can be generated and this slows down the process, so the user may want to turn off automatic figure generation in some situations.

Note that all of the variable names in the controlling variable section start with the prefix *control_* so they are not confused with the other variables that are defined later in the script. Overall, once the controlling variables are adjusted to the user's preference they can run the script and wait for results. This process can take quite a long time, depending on the amount of data.

This function can be used individually to analyze a single data file. It has the following format (shown below in Figure 2.5):

```
[spreadsheet_export_headers spreadsheet_export_row errorcode critical_fileerror]
= epri_truck_data_file_analyze_fcn_v1(control_filedir_load, filename_load,
      control_save_figs, control_fig_save_loc)
```

Figure 2.5 - Format of the Data Extraction Sub-Function for Individual .mat Files

Like the extract all data script, the analyze data script contains the same error code tracking system. The *errorcode* output variable contains numbers that correspond to specific error conditions. This can be a single number, or an array of numbers for multiple error conditions. Note that an error code of 0 indicates that no errors occurred. The *critical_fileerror* output variable will always be a single value that indicates the severity of all of the error conditions encountered and it helps define what actions should be taken by the higher level script. A *critical_fileerror* of 0 indicates that the *errorcode* is more of an advisory to the user and no automated response is needed. A *critical_fileerror* of 1 indicates that some of the .mat data files corresponding to the CSV file may be deleted due to corrupt data. A *critical_fileerror* of 2 indicates that no results from .mat data should be saved for the vehicle and any analysis results previously saved should be deleted. *critical_fileerror* = 2 is the most severe.

The other two output variables contain data analysis results in the form of a cell array row. *spreadsheet_export_row* contains all output values concatenated into a horizontal cell array. This will eventually form a row of data output in the Excel spreadsheet. *spreadsheet_export_headers* contains text headers that correspond to the values in the *spreadsheet_export_row*. The header cell array should be the same size as the row cell array, or else MATLAB will crash.

A controlling variables section also exists in the *epri_truck_data_file_analyze_fcn_v1* sub-function as well as the main script, where key variables that affect the performance of data

analysis for an individual vehicle can be controlled and tuned. This is shown below in Figure 2.6.

Currently, the only value in this section is *min_datapoints*, which controls Error Code 1. This prevents the function from processing any data files with less than the specified number of data points. Additional controlling variables can be added to this section if more complex analysis is added into the data script. For example, maybe there are certain cutoff values that control data filtering or separation steps.

```
%% Controlling Variables
% Use these variables to tune the performance of the analysis function.

% Minimum acceptable number of data points that can be in a .mat file to
% process the file.  This includes all bus message values.
min_datapoints = 300 ;


%% Begin Script - Initialize Workspace
```

Figure 2.6 - Controlling Variables Section in Data File Analyze Function

Since this code is only a data management framework that loads file data and produces basic data statistics, additional data analysis will need to be added into it in the future. Here are the steps that need to happen when an additional data output variable and the corresponding logic are added into the function.

2.3.2 Instructions to Add Data Analysis Code Into the Data Analysis Framework

Note that absolutely no modifications need to be made to the higher level *Analyze_all_truck_data_v1.m* data script for new data output to be added.

Step 1: *Add additional code to produce a new data output in the commented section of code shown below* (Figure 2.7).

The below section of code is where the actual data analysis can be added.

```
%% DATA ANALYSIS - Add additional data analysis code here.

% Create additional sections as needed.
% When creating new output variables, be sure to:
% > Initialize these new output variables in the initialize variables section
where indicated
% > Concatenate the new output variables into the spreadsheet_export_row
% cell array, which will be sent to the higher level script and compiled
% into an excel spreadsheet.  Be sure to define new headers that correspond
% to the indecies in spreadsheet_export_row in spreadsheet_export_headers
% as well.
% > Define the new output variables in the function comments section at
% the top of the script.
% > Add additional print screen output at the end of this script if
% desired, to print results to the screen.
```

Figure 2.7 - Step 1 of Adding Additional Data Analysis

Step 2: *Be sure to initialize any new output variables generated in Step 1 in the "Begin Script – Initialize Workspace" section of code shown below (Figure 2.8).*

If an error code is produced, this ensures that a generic output value will still be produced. This will help prevent MATLAB exceptions that could crash the process.

```
% Initialize Generic Data Output Variables
datapointcount = []; % Count of data points in .mat file
firstdatapoint_serialdate = 0; % first/earliest serial date number in .mat file
firstdatapoint_timestamp = {''}; % first/earliest serial date number in .mat file
converted to time stamp
lastdatapoint_serialdate = 0; % last/ latest serial date number in .mat file
lastdatapoint_timestamp = {''}; % last/ latest serial date number in .mat file
converted to time stamp
vin = 0; % Vin number, extracted from data file name
filenum = 0; % File number, extracted from data file name.  There can be multiple
.mat files for a single vin.
filecount = 0; % Total number of .mat files for a single vin.  This is extracted
from the data filename.

% Initialize specific data output Variable
% ADD VARIABLE INITIALIZATION FOR FUTURE DATA OUTPUT HERE
```

Figure 2.8 - Step 2 of Adding Additional Data Analysis

Step 3: *Concatenate the new data output variables into the* `spreadsheet_export_row` *cell array at the bottom of the script. Define new spreadsheet headers that correspond to the spreadsheet row in the* `spreadsheet_export_headers` *cell array*.

These spreadsheet variables are the function outputs, which will be compiled into an Excel spreadsheet. Note that the variables *spreadsheet_export_row* and *spreadsheet_export_headers* are aligned, to ensure that spreadsheet headers will correspond to the correct data in the Excel spreadsheet. In the below example, there was not enough horizontal space to show the sample code in this format. In the MATLAB software, use the horizontal scroll bar to see the full length of the values in these vectors. The section of code where this is defined is shown below (in Figure 2.9).

```
 % Horizontally concatenate all output variables and header labels into cell
 % arrays.  spreadsheet_export_array must be cell array.  Excel spreadsheet
 % columns will be in the order of data concatenation.
 spreadsheet_export_headers = { 'File Name', 'VIN', 'File Number', 'Number of
Data Files for VIN', 'Error Code Output', 'Severity of Error Code', 'Number of
Data Points in File', 'First Data Point Collected at:', 'Last Data Point
Collected at:', 'First Data Point Collected at (MATLAB serial date):', 'Last Data
Point Collected at (MATLAB serial date):' };
 spreadsheet_export_row = { filename_load vin filenum filecount errorcode_string
critical_fileerror datapointcount firstdatapoint_timestamp
lastdatapoint_timestamp firstdatapoint_serialdate lastdatapoint_serialdate };
 % FOR FUTURE DEVELOPMENT, BE SURE TO CONCATENATE NEW VARIABLES AND
 % HEADERS TOGETHER HERE TO COLLECT RESULTS IN SPREADSHEET.
```

Figure 2.9 – Step 3 of Adding Additional Data Analysis

Step 4 – Optional: *Add new summary statistics print screen in "End of Function Display" section of code (shown in Figure 2.10).*

This will print the data analysis results to the command window, which can then be saved into the overall runlog output. This output is redundant and harder to reference than Excel spreadsheet data, but it could be useful depending on user preferences.

```
 %% End of Function Display

if critical_fileerror == 0 % Output if no critical Error
 fprintf('-------------------------------------------------------\n')
 fprintf('\nData was successfully analyzed from the file:\n\t%s\n\n', fileloc)

 % Summarize selected Output Variables in Print Screen
 fprintf('Summary of output vehicle statistics from analysis:\n\n')
 fprintf('\t%d - datapointcount - Total Number of Data Points in Vehicle File.
\n', datapointcount)
 fprintf('\t%s - firstdatapoint_timestamp - Date/time when the first/earliest
data point in vehicle file was collected.\n', firstdatapoint_timestamp)
 fprintf('\t%s - lastdatapoint_timestamp - Date/time when the last/latest data
point in vehicle file was collected.\n\n', lastdatapoint_timestamp)

 % FOR FUTURE DEVELOPMENT, ADD ADDITIONAL PRINT SCREEN OUTPUT HERE FOR
 % ANY ADDITIONAL OUTPUT VARIABLES ADDED, IF DESIRED.

end
```

Figure 2.10 – Step 4 of Adding Additional Data Analysis

Step 5 – Optional but Recommended: *Update output variable description in the comments at the beginning of the function (shown in Figure 2.11) to include new output variable.*

This will help document what the outputs are for future reference.

```
 % > spreadsheet_export_row - Cell array that contains all output
% variables.  Be sure to include a description of all output variables
% that are compiled into this cell array below:
%
% General Output - applicable to any data analysis:
% > filename_load - This input variable is also provided as an output
% for reference
% > vin - VIN number extracted from file name, for reference
% > filenum - .mat file number, that indicates which .mat file is
% beign processed if there are multiple .mat files per vehicle.
% This is extracted from the .mat filename
% > filecount - Total number of mat files for a vehicle.  This is
% extracted from the .mat file name.
% > errorcode_string - Text string of all error codes produced by the
% data analysis, for reference in the Excel Spreadsheet.
% > critical_fileerror - copy of critical fileerror output to the
% function, for reference in the excel spreadsheet.
% > datapointcount - The total number of data points in the vehicle file
(all
% bus messages).
% > firstdatapoint_timestamp - Time stamp corresponding to first/
earliest data point collected.
% > lastdatapoint_timestamp - Time stamp corresponding to last/ latest
data point collected.
% > firstdatapoint_serialdate = firstdatapoint_timestamp as MATLAB serial
date number.
% > lastdatapoint_serialdate = lastdatapoint_timestamp as MATLAB serial
date number.
%
% Specific output to data analysis:
% Add a description of new specific data output variables here.
```

Figure 2.11 – Step 5 of Adding Additional Data Analysis

If a new error code needs to be added to the shell script and function, follow these steps.

Step 1: *Write code that defines a new unique value for the variable errorcode in the epri_truck_data_file_analyze_fcn_v1.m function if some error condition occurs.*

A section of code to demonstrate this is not provided, because this could occur at many different points in the function code.

When an error code is defined, be sure to update the variable *errorcode* to the new value, or if *errorcode* already has previous errors, concatenate the new variable vertically onto the end of the existing values if multiple error codes should be reported. In addition *critical_fileerror* may need to be updated as well, so the script can take some action. Be careful to not downgrade the severity of *critical_fileerror* if a more severe error code was encountered previously. It is the programmer's responsibility to ensure the data analysis code produces the proper *errorcode* and *critical_fileerror* outputs for all possible error conditions. If statements can be used around subsequent sections of code to prevent execution if an error code has been encountered, or a function return statement can be used. The user will have to design a system to ensure proper errorcode reporting.

It may be a good idea to add some print screen output into the function when the error code is encountered and defined, such as:

```
        errorcode = 1; % Too Few Data Points - All bus messages.
        critical_fileerror = 1;
        fprintf(['ERROR CODE 1: There are too few data points in this file
for data to be analyzed.' ...
        '\nThe file only has %d data points.\nThe File must contain at
least %d data points.\n\n'], ...
        length(time_days_serialnum), min_datapoints)
```

Figure 2.12 – Sample Error Code Output Code

It is recommended to add two new lines '\n' onto the end of the print screen output to maintain spacing.

Step 2 – Optional but Recommended: *Add a new error code description into the output variable description for errorcode in the comments at the beginning of the function.*

This will help document what the new error code value means for future reference.

```
 % OUTPUTS ARE:
% > errorcode - Numeric values corresponding to different error conditions:
% 0 - No error
% 1 - Too Few Data Points - All bus messages.
%
% errorcode can also contain multiple error codes for a single file, if
% multiple errors are encountered.  If this occurs, errorcode should be
% a vertical vector which contains all the error codes produced.  It is
% the programmers responsibility to ensure that errorcode always
% produces the appropriate output when modifying this script.
```

Figure 2.13 – Step 2 of Adding Additional Error Codes

Step 3: *Script Changes – Add new print screen output into the higher level Analyze_all_truck_data_v1.m script that lists which files produced the error code at the end of script execution. This will print the errorcodes produced by all .mat files into a summarized list.*

Match the format of existing error code print screen outputs. The value of *errorcode* outputted by the function needs to be updated in the following highlighted locations. This is critical to ensure proper output.

The example below (in Figure 2.14) is an error code which does not exist in the current script format, but provides an illustrative example. Also, update the print screen description so an appropriate message is displayed.

```
 % Display all Error Code 3 files
 if length(find(track_errorcodes(:, 2)==3)) > 0
       fprintf(['Files Producing ERROR CODE 3: Vehicle file contains multiple VIN
numbers in discrete value data.  \nThere' ...
       ' should only be 1 VIN number per vehicle file.\nNo data from this VIN
number will be saved in analysis results.\n\n'])
       % Display the names of all files that produced error code 3.
       fprintf('\t%s\n',
data_directory_filenamelist_raw(track_errorcodes(find(track_errorcodes(:, 2)==3),
1)).name)
       fprintf('\n')
 end
```

Figure 2.14 – Step 3 of Adding Additional Error Codes

Additional actions do not need to be taken to compile error codes. This will be done automatically when any error code is detected. Error codes are tracked in the variable *track_errorcodes* in the *Analyze_all_truck_data* script, where the first column corresponds to an index in the *data_directory_filenamelist_raw.name* structure that lists each vehicle file, the second column contains the actual error code, and the third column corresponds to the value of *critical_fileerror* to define severity.

2.4 Future Work That Could Improve the MATLAB Big Data Analysis Framework

Although the data analysis framework was used successfully, there is always room for additional improvement. This section outlines future work that could be implemented to make the data analysis framework even more robust and useful to future projects. There is a huge advantage to having efficient, clean, and robust code. Although it takes longer to develop, it can prevent major hassles down the road when it is finally implemented and used. Here are some suggested areas where the described software can be improved:

1) Parallel processing could be implemented into the data analysis framework using MATLAB's parallel computing toolbox [34] and it could be run on a computer cluster. Currently the code runs on a single core and can take days to process all of the data. However, since each data file is processed independently, in theory it

should be relatively easy to run the analysis in parallel on a computer cluster. It is likely that the for loops would need to be changed into parfor loops and distributed arrays would possibly have to be used to collect output. It is also possible to run MATLAB on a Hadoop Cluster [35].

2) Reduce hard coded values that control the data extraction CSV input format. It should be easy to modify the data extraction script to accept different CSV formats, but there is no centralized system that controls the input file format. All of the values related to format should be collected into one location, similar to the controlling variables section. Maybe these could be grouped together into a separate data format definition script that launches from the main script.
3) MATLAB structures could be used to group similar variables together.
4) A Try / Catch statement could be implemented around the section that loads data files, in case the file system becomes unavailable. This could also be placed inside of a loop, so the system will continue to try and load the data until it becomes available. Occasionally, there were issues where a network issue would make our folder structure containing our dataset unavailable.

SECTION 3

INITIAL FEASIBILITY ASSESSMENT OF USING THE EPRI VEHICLE TRACKING DATA TO ANSWER POTENTIAL RESEARCH QUESTIONS

3.1 Introduction to the Feasibility Assessment

A feasibility assessment was conducted in the Fall of 2014 on some of the preliminary data to better understand what kinds of questions could be answered. The work in this section laid the foundation for this future work. Below is a list of the questions that were evaluated for feasibility. Not all of these questions were analyzed as many are very complex data analysis problems, so this section just outlines some theoretical approaches that could be used to attempt to answer the questions and what CAN signals might be needed. However, it was a good initial exercise to identify what questions might be the most feasible and valuable to answer, and what approach might be taken. This provided a guide to help determine which problems were to be analyzed later in this thesis. Here is a list of the questions that were evaluated. Questions in ***italic-bold*** text are examined and analyzed in some form later in this thesis.

- ***How efficient are the vehicles?***
- ***What is the effective range of the vehicles?***
- ***How much energy do the vehicles use?***
- What kinds of utility load shapes do we see when the vehicle is charging?
- ***What is the Utility Factor (UF) for the Vehicles?***
- ***How does HVAC affect vehicle performance?***
- ***How often were the vehicles charged over a certain period of time?***

- How long did the vehicles go between charges? How long were they charging?
- ***How often was the vehicle driven? In general, how far was a trip?***
- Did vehicles mostly travel between a handful of "unique" places, or were driving patterns more scattered? Were most trips between a couple of locations?
- Define some kind of assessment of vehicle performance (perhaps a combination of a couple of things such as efficiency or use depleting and charging of the battery).
- ***Show a comparison of the different vehicles, perhaps highlighting why they are or are not different.***
- How much energy is recovered by regenerative braking?
- ***How do climate and weather conditions affect vehicle performance and driving patterns?***

It is important to keep in mind that the information presented in this section only provides an initial feasibility assessment. If more data analysis and feasibility assessment were performed, more information would become available and feasibility assessments and analysis approaches may change. Unexpected problems that cannot be anticipated could still be encountered. However, this section also provides an important foundation to identify which questions make the most sense to answer and provides a starting point to answer those questions.

The remainder of this section provides a detailed discussion about each of the questions outlined above. This discussion provides insight into the methods that might be used to answer these questions and what CAN signals might need to be collected from a vehicle to make the analysis feasible.

3.2 Category: Questions Related to Energy Usage / Efficiency of the Vehicles

3.2.1 How Efficient Are the Vehicles?

Vehicle efficiency can be addressed by examining the length of charge-depleting trips, or energy used per mile. Distance traveled, gasoline consumption, and battery charge depletion data are needed to answer this question. Energy consumption from vehicle charging, or energy usage by the motors and engine can also be used.

A metric is needed to determine distance traveled. An odometer signal could be used to measure distance traveled. GPS data could also be used to estimate distance traveled. Or vehicle speed CAN data can be integrated to determine the distance traveled. Since speed data is being collected at a 1-second sampling frequency in the EPRI Commercial Truck dataset, this could be fairly accurate, but with no other metrics to determine the distance traveled there is no way to verify the accuracy of the estimation. The lack of either odometer or GPS data to determine the distance traveled significantly lowers the feasibility of performing this analysis.

A CAN signal for the fuel tank level could be useful to help determine how much gasoline was used by the vehicle. The rate of fuel consumption should correspond to the power used by the vehicle engine. Since the engine will only use a very small amount of fuel on a second-by-second basis, it may not be possible to observe the changing engine power requirements on this time scale using the fuel tank level signal. The fuel level sensor is most likely not accurate enough to see how the fuel level in the gas tank is changing over seconds or minutes and is likely only useful to determine fuel consumption over longer time periods. Monitoring the fuel injection flow rate through the fuel injectors on the engine could provide a more accurate measure of fuel consumption over short time periods.

Engine power can also be estimated from engine speed and torque if those CAN signals are available. If the OBDII system on a vehicle platform can measure engine torque directly, this could be useful. A correlation between vehicle torque and the CAN-communication bus signal for throttle position could possibly be determined. However, in a hybrid vehicle with a parallel or power-split powertrain configuration [2, 13], it may be difficult to determine if the torque request from the driver is being directed to the engine or the electric motors without additional information. Another problem is that the power output from the engine driveshaft will be much less than the energy content of the fuel that is flowing into the engine, as internal combustion engines generally have efficiencies of about 25% [36, 37]. The engine efficiency also varies depending on what speed and torque it is being operated at [13]. To estimate fuel consumption from the engine speed and torque, detailed information mapping the engine efficiency across the operating range of engine speeds and torques would also be needed. It is possible that this kind of engine test data could be acquired from an outside source depending on the vehicle platform.

To calculate electric charging efficiency, it would be best to use the charging station current and voltage CAN signals, as these are believed to represent the power being drawn from the grid by the vehicle charger. Using the AC current and voltage values from the electric grid that are going into the charging station is probably best, as these measure AC electric powers before any power loss occurs due to the AC / DC converter or other components in the vehicle charger. There may also be other CAN signals that measure the DC power after the power goes through the AC / DC converter in the vehicle charger.

Electric power drawn from the battery can be calculated by multiplying the CAN signals for the main vehicle battery current and the voltage. If this is monitored on a second-

by-second basis, instantaneous power consumption can be estimated. The electric energy coming out from the battery may not be the same as the electric energy needed to charge the battery, as there will be some energy loss when the battery is charged.

Another method to determine electric motor power could be to use CAN signals that correspond to the rotational motor speed and the motor torque. Many hybrid vehicle models have two electric motors (which also function as power generators) [2, 38, and 39] so torque and rotational speed would be needed for each motor. Motors generally have much higher and uniform efficiencies than engines and they generally convert about 75% of electric power into mechanical power [13, 37, and 40].

If data is being collected at different points along the electric power path through the vehicle, it may be possible to determine the electric efficiency of different electric components in the vehicle. This would be done by studying the energy losses across those components. Specific pieces of hardware for which the energy efficiency could be calculated include the AC / DC converter in the charger, the battery, and the electric motors.

In addition, to calculate the driving efficiency, the time periods over which the vehicle is driving first need to be identified in the data. Checking if the vehicle speed is greater than zero could be one method to identify these driving events. Or a key on/off signal could also be used.

This question of calculating the vehicle efficiency and fuel economy is investigated and analyzed further in Section 5 and results are presented.

3.2.2 What Is the Effective Range of the Vehicles?

To determine the effective range of a Plug-in Hybrid Electric Vehicle (PHEV), charge-depleting trips need to be identified. The CAN signal for battery state of charge (SOC) can be used to identify when the battery reaches depletion. The exact SOC level where the vehicle platform transitions from a charge-depleting to a charge-sustaining mode depends on the vehicle platform.

In addition to state of charge, a metric is needed to determine distance traveled. An odometer signal is likely the best way to measure distance traveled. GPS data could also be used to estimate the distance traveled by calculating the distance between consecutive GPS data points. Or a vehicle speed CAN signal could be integrated over time to determine the distance traveled. Since speed data is being collected at a 1-second time interval in the EPRI Commercial Truck data, speed integration could be an accurate estimation for this dataset. However, it is also recommended to collect either odometer or GPS data to compliment the speed integration so the accuracy of the calculation can be verified.

3.2.3 How Much Energy Do the Vehicles Use?

This question is very similar to the question "*How Efficient Are the Vehicles?"* which was previously discussed in Subsection 3.2.1 and has the same requirements for data collection. As a matter of fact, determining how much energy vehicles use is a prerequisite to determining their efficiency. Again, see this previous Subsection 3.2.1 for more information about what is needed to determine energy usage.

The feasibility of this question is likely higher because the overall amount of energy used per vehicle does not depend on distance traveled. However, odometer, speed, or GPS

information that can be used to calculate distance would still be very beneficial, as energy used per mile might be a more useful number.

3.2.4 What Kinds of Utility Load Shapes Do We See?

This question can be addressed by referencing charger voltage and current information and the timestamps associated with these events. A utility load shape is the graph of the power load on the power grid over time.

3.2.5 What Is the Utility Factor for the Vehicles?

To determine utility factor [41], it needs to be determined whether the vehicle is in a charge-depleting mode or a charge-sustaining mode [2, 11]. The vehicle is using battery power in charge-depleting mode, while it is using engine power in charge-sustaining mode. This can be done by monitoring the battery SOC signal for low values that indicate a transition from CD to CS mode and by using an engine RPM bus message to determine when the engine is turned on. Alternatively, the SAE J2841 methodology can be used with only daily-driving distance data [60].

This question is further investigated in Section 4 and utility factor results are provided for the EPRI Medium-Duty Truck dataset.

3.2.6 How Does HVAC Affect Vehicle Performance?

Using AC systems in the vehicle is known to decrease vehicle performance and efficiency [42, 43]. To measure the impact of these systems in the real world, data needs to be collected for the heater and/or AC systems. Another reason to monitor HVAC use is that it is

know that in some PHEV vehicles, the engine turns on when its heater is running [44, 45]. Engine rotational speed and ambient temperature CAN signals could be used to determine when the engine is turning on at cold temperatures vs. warm temperatures, and how this correlates to HVAC and vehicle performance.

This question is discussed and analyzed further in Subsection 5.6.3.

3.3 Category: Questions Related to How the Vehicles Were Used

3.3.1 How Often Were the Vehicles Charged Over a Certain Period of Time?

Charging events need to be identified in the continuous stream of data, likely using charging station or charging port current and voltage CAN signals to see when the vehicle is plugged in and when power is being transmitted to the vehicle.

An algorithm to calculate charging events is presented in Section 4.

3.3.2 How Long Did the Vehicles Go Between Charges? How Long Were They Charging?

Again, charging events need to be identified in the vehicle operating mode column. Then, the length of the charging events and the time between them can be averaged. Time stamp information will need to be used. Charging station current and voltage signals could also be used to determine when the vehicle is charging based on raw data signals.

3.3.3 How Often Was the Vehicle Driven? In General, How Far Was a Trip?

To answer this question, there needs to be a way to determine when the vehicle is driving in the data stream. Vehicle speed CAN information could be monitored for values greater than zero, which would indicate driving.

Distance traveled would also need to be determined. An odometer CAN signal is likely the best way to measure distance traveled, as this is the legal definition of the value. If these values are not available, GPS or speed integration could also be used. With high-sampling rate data collected at 1-second intervals in the medium-duty truck data, this could be very accurate, but it would be impossible to verify the accuracy without another signal. The lack of either odometer or GPS data to determine the distance traveled would significantly lower the feasibility of determining how much distance is traveled during trips.

3.3.4 Investigate Driving Patterns

Did vehicles mostly travel between a handful of "unique" places, or were driving patterns more scattered? Were most trips between a couple of locations? Describe general trends in driving habits without providing detail on specific vehicles.

GPS data is required to answer these questions. The location of the vehicle would need to be identified for this type of analysis.

To improve this type of analysis if GPS data is available, it may be helpful to survey the actual vehicle drivers in the fleet to identify the locations they consider to be home, work, the grocery store, etc. If this additional information can be collected from drivers, instead of just studying time spent going between frequently visited locations, it would be possible to actually define time spent driving from home to work, or home to the grocery store, etc.

3.4 Category: Questions Related to Utility Fleet Health Assessment and Performance

Overall, the questions in this section are much more advanced and the answers will be based on the results of the questions that were reviewed previously. Many of these questions cannot be answered until questions in the *Questions Related to Energy Usage / Efficiency of the Vehicles* in Subsection 3.2 are answered, such as *"How much energy do vehicles use?"*

3.4.1 Define Some Kind of Assessment of Vehicle Performance (Perhaps a Combination of a Couple of Things Such as Efficiency or Use Depleting and Charging of the Battery)

If previously reviewed questions are answered, some sort of diagnostic method could be determined to combine the results from the other questions to determine vehicle performance metrics.

Another interesting study could be to look at charging locations. If a vehicle charges in a certain location, this could be designated as a charging location and it could then be seen how frequently the vehicle charges again if it returns to and parks in this location. GPS location data is required to answer this question.

Kinetic Intensity (KI) could be investigated to measure driver aggressiveness. Kinetic intensity is defined at the ratio of positive characteristic acceleration to the square of aerodynamic speed [46]. High kinetic intensity values indicate that positive acceleration events are dominant, while low kinetic intensity values indicate driving behavior dominated by cruising at high speeds. A high-data sampling rate, such as 1-second sampling frequency data, is required to see the short term acceleration events that are needed to calculate kinetic intensity. A CAN signal for throttle position could also possibly help identify driver aggressiveness and acceleration events. To improve the accuracy of a kinetic intensity

calculation, a CAN signal for vehicle acceleration could also be used if it is available. This would prevent the differential of speed from being taken. For more accurate results, the change in height or gradient can be factored into the vehicle acceleration equation. GPS data could be used to calculate change in altitude between points as the vehicle goes up and down gradients.

3.4.2 Show a Comparison of the Different Vehicles, Perhaps Highlighting Why They Are or Are Not Different

This question is very broad, which increases its feasibility. Metrics such as standard deviation could be determined to quantify deviations between all the vehicles in a fleet for different values such as average speed, efficiency, etc.

Case studies could be provided for a few interesting vehicles to provide a close up view of a small subset of the data. Since there would be privacy concerns with publishing detailed information about the driving habits of specific drivers, this would only be possible if legal authorization were obtained from some of the drivers to be included in these case studies. Obtaining legal authorization to publish information about the driving habits of specific drivers would be very beneficial to the goals of any research project, as understanding the behavior of individual vehicles in the dataset can supplement the high-level fleet-wide view created from mining all of the data. Illustrating the differences in driving behavior between specific vehicles could provide additional insight into how the fleet is being used.

If legal authorization to publish case studies based on a few individual drivers can be obtained, these case studies could be further supplemented by integrating softer datasets into the hard data collected by the vehicle tracking system. This softer data could include

interviews with fleet drivers about their experience, or self-reported driving information similar to the NHTS survey [47]. Although this type of information is generally not as concrete or as accurate as electronically gathered data from sensor networks, it is also a more flexible data collection system that may be able to identify unforeseen trends that are not being monitored by the electronic system. When you just ask people about their experiences, you do not have to anticipate what kind of an answer you will be getting such as when you are trying to configure an electronic system of sensors. This could help identify gaps in the electronic data collection system, or it could also help record information that cannot possibly be collected by sensors such as "driver satisfaction." This type of softer information could also be used to understand why trends in the electronic data occur. For example, maybe Driver A has a different work schedule than Driver B and this could only be verifiably determined by interviewing fleet drivers directly.

3.5 Category: Additional Questions That Could Be Interesting to Study

3.5.1 How Much Energy Is Recovered by Regenerative Braking?

The high 1-second data collection rate in the EPRI Medium-Duty Truck dataset should allow for these short term braking events to be identified. Electric current traveling from the battery to the electric motor will be negative when these events occur, since the motor is operating as a generator and sending power back to the battery.

In addition to a throttle position CAN signal, it could be helpful to have a brake position CAN signal for this kind of analysis. This would help confirm when brakes are being used.

3.5.2 How Do Climate and Weather Conditions Affect Vehicle Performance and Driving Patterns?

An ambient temperature CAN signal would likely be very helpful to determine the climate conditions in which the vehicle is operating. If there are outside humidity or barometric pressure sensors on the vehicle, it could be helpful to collect data from these sensors as well to construct a more complete picture of the current weather conditions. For this type of analysis, GPS data could also be very helpful, as it could in theory be cross referenced with a historical weather database to pull up temperature and weather conditions at a specific point at a specific time. This could help determine if other weather events that cannot be recorded by current vehicle CAN sensors, such as rain or snow conditions, are occurring. GPS information could also help identify changes in driving habits based on locational information. In addition to GPS, it would also be very helpful to have odometer information, as this could be used to determine distance traveled during full charge-depleting trips. Distance traveled during charge depletion can be used as a metric of performance and efficiency.

The correlation between ambient temperature and fuel economy is further explored in Section 5 and results from this analysis are presented in Subsections 5.5.1, 5.5.2, and 5.5.6.

3.6 Comments on Data Sampling Frequency

Higher data collection rates should improve the accuracy of all calculations. Greater detail can be seen when data is collected at smaller time intervals so short-term vehicle events can be analyzed. To better understand what this means, states of vehicle operation can be thought of in two categories: long-term super states and short-term control states. Super states include longer term events such as EV vs. HEV mode, plug-in charging events, transmission

gear, drive, park, etc. Control states include short-term events such as fuel-injection rate changes in the engine, vehicle acceleration, braking, steering, etc. A lower data collection rate, such as data that is reported every minute, is sufficient to see the long-term super states. However it cannot identify the short-term control states. A higher data collection rate allows for an analysis of both super states and control states, which will broaden the scope of possible analysis that can be performed with the data.

The disadvantages of a higher data collection rate include the memory size and processing power required to analyze the collected data. In addition, when more data is collected, there is a higher probability of rare and obscure errors occurring in the data which may need to be filtered and protected against. Depending on the nature of the research question, a decision will need to be made on what data collection rate should be used. However, it is always possible to summarize a large dataset, but it is not always possible to collect more information if the data collection rate is too low, so it is generally better to use a higher data collection rate if the resources are available to do so.

SECTION 4

DATA MANAGEMENT FOR GEOGRAPICALLY AND TEMPORALLY RICH PLUG-IN HYBRID VEHICLE "BIG DATA"

4.1 Summary of Work

This section details some of the data management algorithms that were developed to manage and derive results from the second-by-second medium duty truck dataset. I would like to give special thanks to Zachary Wilkins for helping develop the charging and driving event identification algorithms and for developing much of the code to calculate these events while under my guidance. Zack was able to finalize and test the event identification algorithms based on the data management and analysis framework that I had developed previously and which is described in Section 2. He also developed the formula for the alternative utility factor calculation and generated the code to calculate and display the results. I was then responsible for reviewing the code, fixing a few bugs, writing up the scientific paper, and determining the conclusions of the work. Also, special thanks to Mark Kosowski at EPRI for providing us with the data for this study and overseeing the data collection project in general. Finally, special thanks to my advisor Dr. Thomas Bradley at Colorado State University for providing me with guidance and insight to develop this paper. Much of the text here in Section 4 was published in the Electric Vehicle Symposium 29 (EVS29) conference paper entitled *Data Management for Geographically and Temporally Rich Plug-in Hybrid Vehicle "Big Data"* on which I was the primary author [1]. There have been only minor changes to the paper in this thesis and some additional material added to the original text.

The Electric Power Research Institute (EPRI) and its project partners have developed some of the highest sampling frequency and most complete light- and medium-duty plug-in hybrid electric vehicle truck operational data for Odyne and Via trucks. This data was collected through a CDMA / GMS transmitter plugged into the CAN-communication bus of the fleet. This section discusses the process of transforming these raw datasets into a scientific database of driving and charging events using data quality management, filtering, processing and decision support tool development. The result is a dataset with demonstrable utility for vehicle design, policy analysis, and operator feedback.

4.2 Introduction

The Electric Power Research Institute (EPRI) and the US utility industry are interested in understanding the means by which grid electricity will enter the transportation energy sector. The quantity, timing, and statistical distribution of electricity consumption have near- and long-term effects on utility planning for loads, assets, profitability, and sector growth [2, 48].

In the near-term, the function of the various types of OEM (original equipment manufacturer) electrified vehicles that are for sale is the most effective indicator of how consumers will use electrified vehicles [2, 15, and 49]. To gather data on the function of these vehicles and the behavior of their users, EPRI and the US Department of Energy have developed a program to gather and store GPS (geographical positioning system) derived location data along with detailed vehicle operation data from a sample set of light- and medium-duty PHEV trucks being utilized as utility bucket trucks and general support trucks [15]. Because of the very large scope of this effort, there exists a need to synthesize these large

datasets into databases and toolsets that can communicate the results of these studies to researchers and stakeholders.

With the development of distributed data collection technologies, many other researchers have developed techniques to collect, store and synthesize operation data from vehicle fleets [15, 43, 48, 49, 50, 51, 52, 53, 54, 55, 56, and 57]. Characterizing the operation of PHEVs is of particular interest to transportation system researchers because of the well-documented dependency of vehicle fuel consumption on individuals' driving and charging habits [41, 48, 49, 50, 52, 53, 55, and 58]. In many previous studies [48, 49, 52, and 53], datasets have relied on the data collected from private individuals and have therefore encountered privacy and traceability concerns. In this study, we have collected vehicle operation data from commercial light- and medium-duty vehicles. In general, these vehicles represent a unique study subset of the US vehicle fleet that has not been studied in detail before. In addition, because these are fleet-owned vehicles, the collection of correlated GPS and vehicle operational data does not present as many privacy concerns.

On the other hand, the increased scope of this data collection effort has led to a variety of technical and "big data" management challenges that have been addressed. In discussing the "reality" of these data collection projects, their limitations, and the technical means used to generate results from them, this chapter seeks to improve and contribute to the state of the art in the field of large-scale big data transportation system data collection projects.

Colorado State University (CSU) has developed an algorithm to identify drive and charge events from the raw vehicle data files with the 1-second data sampling frequency. These results can be viewed directly in an Excel spreadsheet format with charts as demonstrated in the *Decision Support Tools Development* Subsection 4.3.6, or used for

additional scientific analysis, as demonstrated in the *Application of Summarized Dataset and Results* Subsection 4.4. By summarizing the low-level high frequency data into a list of higher-level events, the data size can be greatly reduced into a format that provides great utility for answering policy, vehicle design, and operational questions about the vehicle fleet using significantly less computational power.

4.3 Methods

4.3.1 Dataset and Project Overview

In this project, EPRI and CSU sought to summarize the very large raw dataset to produce a smaller subset of data with immediate utility to answer policy, design, and operational questions about PHEV vehicles. This summary data was then used to calculate the actual energy consumption of these light- and medium-duty vehicles, investigate charging frequency, and generate utility factor curves. This was done using vehicle-derived data, including driving distance, battery state of charge, fuel injection rate into the engine, charging station power, and more.

4.3.2 Data Management and Quality

The dataset was originally downloaded directly from EPRI's main database hosted on Amazon Redshift using an R script with embedded SQL. The Amazon Redshift database already had some low-level filtering applied to the data to eliminate known bad sensor data. The SQL embedded in R was used to filter out irrelevant CAN signals at the very beginning of the analysis, so they would not have to be parsed through later in the resulting CSV files.

These R scripts created a single CSV file for each vehicle month, which were then processed in MATLAB.

The first step of the MATLAB processing involved converting the CSV data into a .mat file data format and performing some basic data validation. Resaving the data added time to the overall processing sequence, as the data had to be written to and read from the disk an extra time. However, it was also generally more beneficial to save intermediate data, so that later processing steps could be rerun without reprocessing all of the data through the preliminary steps. Due to the large file size, a feature was built into the code that would only read in a portion of a CSV file to break up those files into multiple .mat files. These .mat files could then be loaded individually into the computer memory for analysis to avoid overloading the available RAM.

Basic data validation was also performed in this preprocessing step. The basic data validation primarily verified the data file format, such as correct number of table columns and proper delimiters. Most of the data was properly formatted, but it was also important to remove even very uncommon errors to prevent later analysis scripts from crashing. This data cleaning made the general analysis process more robust.

4.3.3 Data Processing and Filtering - Compiling Driving Events List from Raw Data

To analyze the raw data into meaningful results, the data processing and filtering steps were closely integrated. Often, the data was re-filtered after each processing and analysis step. This section walks through the process of how the raw 1-second sampling frequency data was converted into a meaningful list of vehicle driving events. These driving events were also presented along with associated statistics, such as trip distance, time duration, energy usage,

and State of Charge (SOC). Then, the next Subsection 4.3.4 shows how this algorithm to identify driving events can be modified to identify charging events.

The biggest challenge to identifying these drive events was data quality, as there are some situations where the data for an event is incomplete. Therefore, it is critical for this algorithm to be reasonably robust when applied to imperfect data that contains some errors, while remaining effective enough to still produce realistic results.

A drive event is considered to be a single vehicle trip starting when the vehicle begins moving and ending when the vehicle stops moving. Each drive event is recorded in a single spreadsheet row, along with additional information about the date, the time, the trip duration, the distance traveled, the fuel and electricity consumption, the initial battery state of charge, the final battery state of charge, and information identifying the individual vehicle.

The drive mode for each vehicle was also identified along with each drive event and these are categorized as charge-depleting (CD), charge-sustaining (CS), or blended driving modes. A charge-depleting mode is when the vehicle is driving only on battery power and this drive mode is powered by energy from the electric grid. A charge-sustaining mode is a traditional Hybrid Electric Vehicle (HEV) mode, in which energy from the gasoline engine is recaptured and stored in the battery and the source of vehicle energy comes from conventional gasoline. A blended drive mode is a variation of charge-depleting mode where the gasoline engine is used to slow the rate of battery depletion and the vehicle is operating on both grid and gasoline energy. For Odyne, the vehicle only operates in a blended and CS mode, so there is no CD mode on Odyne [15]. On Via, the vehicle only operates in CD and CS modes and the blended mode is used to categorize driving events where the vehicle transitions from CD to CS

mode [15]. How the driving modes are defined could also be further refined in future analysis work.

Data processing and filtering began after the data was converted into a MATLAB data format, as described previously in the *Data Management and Quality* Subsection 4.3.2. When the analysis was run, any individual vehicle data file that had less than 5000 logged data points in a month was removed from the analysis. These small data files could have been the result of vehicles that were never driven or vehicles that did not have a functional tracking system installed. Then, the following data points for relevant CAN-communication bus messages were extracted: vehicle speed, vehicle odometer, battery state of charge, vehicle charging station voltage (when vehicle is being charged), vehicle charging station current, and engine fuel injection rate.

Once these messages were extracted, each signal was run through a time stamp filter that removed duplicate timestamps. This step was very important, as occasionally there were multiple different values reported at the same time for a single CAN-communication bus signal. These multiple reported values caused significant problems later in the data analysis script if not removed. The algorithm kept the first reported value and removed the rest.

Next, the data points from the fuel injection rate, battery voltage, battery amperage, and battery SOC were interpolated onto the timestamp values for vehicle speed using linear interpolation. Since the data was collected asynchronously, interpolation was a good method to realign and project all of the data vectors for different signals onto a single time stamp value. Vehicle speed timestamps were used for the projection target because these data points were generally only recorded when the vehicle is driving.

Drive events and modes were then estimated based on the following criteria:

1) Vehicle speed greater than 0.01 mph was considered driving (vs. other events in the data such as charging, etc.). An alternate method might have been to use a key on/ off signal, but unfortunately this CAN signal was not added into the data collection system until after this algorithm was developed and data was already downloaded onto CSU machines.
2) Charge-Sustaining (CS) mode occurred when the battery was at less than 5% SOC for Odyne and was at less than 22% SOC for Via. These numbers are defined in EPRI's technical report [15]. It should be noted that for Odyne, 0% SOC is defined as the minimum charge level allowed by the vehicle's control system and it does not represent a true 100% battery discharge that would be detrimental to battery performance.
3) Charge-Depleting (CD) mode occurred when the vehicle was driving and not in Charge-Sustaining Mode.

See the sample MALTAB code below (in Figure 4.1) to illustrate this logic process. Note that these steps were applied to all of the raw data points collected at the 1-second sampling frequency. Later on, once more information was compiled about the driving events, the CD and CS modes were redefined.

```
% Filter for identifying all drive events
Drive_Filter = Drive_Speed > 0.01;

% State of charge limit for CS Mode in Battery % SOC
CS_SOC_Limit = 5; % Odyne
% CS_SOC_Limit = 22; % Via

%% Primary Filters
% A CS Event is when the vehicle SOC is below the CS SOC Limit
CS_Filter = (Drive_Filter & Drive_SOC < CS_SOC_Limit);

% A CD Event is any time the vehicle is driving and is not in CS mode
CD_Filter = (Drive_Filter & ~CS_Filter);
```

Figure 4.1 - Sample MATLAB Code to Illustrate the CD and CS Filtering Process

Next, to find the start and end locations for each drive event, the script looked for a change in the vehicle trip conditions where the drive conditions transitioned from true to false in the list of all raw data points. This was done by creating a logical vector based on the drive criteria, offsetting the values by one index value to create another offset vector, and then subtracting the vectors. Any non-zero value in the resulting vector indicated a change in driving conditions and the sign of the value indicated whether the vehicle started or stopped driving. To augment this method, a secondary method was also implemented to identify large gaps between timestamps greater than 300 seconds. Any event with a time stamp gap greater than 300 seconds was split into two different events at the time gap, as it was assumed that the lack of recorded data indicated that the vehicle was not running. Note that the data collection system installed on the vehicles only recorded data points when the vehicle was in operation or charging. If any of the start and end times for an event were equal, that event was removed from the dataset. Next, if any 2 events took place less than 120 seconds apart, they were recombined into a single event, as a stop of less than 2 minutes was considered inconsequential. Finally, any drive events with less than 5 data points were removed to prevent small idiosyncrasies in the data from being recorded as significant events. Filtering out these

small blips in second-by-second sampling frequency data was very important, because there were often small anomalies in the data that added noise to the bigger picture. Combined, these methods robustly identified events when the vehicle was driving.

Once the start and end times of drive events were located, those starting and ending timestamps (or index values) were used to locate other relevant information from the dataset to calculate statistics of interest for any particular driving event. The statistics calculated for each event include distance traveled, fuel used, electric energy used, change in SOC, the start time and date, and the event duration. A trapezoidal integration was also used to find the integrated values of some variables, such as fuel use, distance traveled, and electric energy usage when only the time-rate signal was available. Note that speed was integrated to calculate distance even though an odometer signal was available because some of the Via odometer data was known to be faulty. Ideally, an odometer signal should be used to calculate distance if it is available, but that was not the case for this dataset.

At this point, some of the previously defined charge-depleting trips were redefined to be either a blended or charge-sustaining mode, based on additional information from the relevant summary statistics for each event.

For this data analysis, a vehicle charge-depleting trip was redefined as blended mode when:

1) The delta SOC for a previously identified charge-depleting trip was negative (i.e. charge was decreasing),
2) The fuel consumption was positive, and

3) The initial SOC was above the CD / CS transition SOC that was set at 5% for the Odyne analysis and 22% for the Via analysis, based on the transition limits defined in EPRI's report [15].

Charge-depleting trips were redefined to be in charge-sustaining mode based on the following criteria:

1) Delta SOC increased over the duration of the event.
2) Fuel consumption was greater than zero and the vehicle was not in blended mode.

Every other condition was considered to be a charge-depleting mode. See the sample MATLAB code below (in Figure 4.2) to illustrate this logic:

```
Blended_Condition = ((CD_SOC_Delta < 0) & (CD_Fuel > 0) & …
 (CD_SOC_Initial > CS_SOC_Limit));
CS_Condition = (CD_SOC_Delta >=0 | (CD_Fuel > 0 & ~Blended_Condition));

for Iteration = 1:number_of_charge_depleting_events
    % Determine Drive Mode
    if Blended_Condition(Iteration)
        CD_T_Mode{Iteration} = 'Blended';
    elseif CS_Condition(Iteration)
        CD_T_Mode{Iteration} = 'CS';
    else
        CD_T_Mode{Iteration} = 'CD';
    end
end
```

Figure 4.2 - Sample MATLAB Code to Redefine Driving Modes

This last step produced the final values used to define the driving event modes in the event summary spreadsheet. The final results were then exported into an Excel spreadsheet format. This completed the data processing and filtering needed to identify drive events.

These results can be reimported into MATLAB for additional analysis or viewed as a stand-alone document.

4.3.4 Data Processing and Filtering - Compiling Charging Events List from Raw Data

The algorithm used to identify charge events is similar to the algorithm used to identify drive events. For this analysis, a charge event is considered to be a time duration when power was being delivered to the battery from the charging station. Alternatively, a charge event could possibly be defined as a time when there was a voltage across the charging station. Using only voltage would account for time when the vehicle was plugged in but already fully charged, as power transfer stops when the battery is full.

Charge events are also identified as Level 1, Level 2, or Level 2+ charges, which depends on the charging station type. A Level 1 charger has a charging level of 120 volts, a Level 2 charger has a charger voltage of 240 volts, and a Level 2+ charger has a charger voltage of 240 volts with a power greater than 3.3kW [59]. The charge level for charging events was determined by finding which of the rated charging station voltage levels the actual charging voltage signal was closest to.

Here are some notable differences in the charging events summary calculation when it is compared to the driving events summary calculation:

1) This calculation used CAN signals for the charging station voltage, charging station current, and vehicle battery SOC.
2) A vehicle was considered to be in a charging event when:

a. The charging power was positive and greater than 100 watts. Charging station power was calculated by multiplying the charging station current signal by the charging station voltage signal.
b. The duration of the charging event was greater than 2 minutes.

3) All signals were interpolated onto either the charging station voltage or charging station current signal timestamps. The projection target was chosen to be the signal with the most time stamp values.
4) Any event with a time stamp gap greater than 2400 seconds was split into two different charging events at the time gap. Any two events with a time stamp gap of less than 2400 seconds were combined into a single charging event.
5) Charging events with no change in SOC were removed. Then, the final state of charge was defined as the maximum SOC for the charging events, due to errors caused by approximating end locations of the charging event. This removed some negative delta SOC values. After the final SOC was redefined, any charging event that still had a negative change in SOC was removed.

4.3.5 Code Validation

Result validation is very important to the data analysis process. Just because a data analysis script reads in data and produces numbers does not guarantee that those results are useful or accurate. Therefore, it is critical to build validation tools into the data analysis script to track the script execution process so intermediate steps can be evaluated. Below is a list of some of the validation tools that were developed for this project. Section 2 of this thesis provides more information about these data validation features as well.

- A system to track custom error messages was embedded into the script, so that problems with individual files could be traced back to a specific point in the dataset. The data analyst still had to define and program the error code definitions into this framework, based on their discretion.
- There was an option to easily create custom graphs of intermediate data from the data analysis process for each vehicle.
- A run log of console print screen output was also recorded. It was up to the data analyst to add print screen statements into the code to document the script execution process in a useful manner.

4.3.6 Decision Support Tool Development

Once the raw data was compiled into an event summary spreadsheet, it was very easy to post-process the data into charts and figures. Additional software could be written to visualize the data, such as a web app, or the data can be processed directly in Microsoft Excel. Below in Figure 4.3 are some sample Excel graphs to demonstrate how the event summary data can be quickly visualized to support fleet management decisions, vehicle design, public policy, and research questions. Excel pivot charts and tables were used to create these graphs.

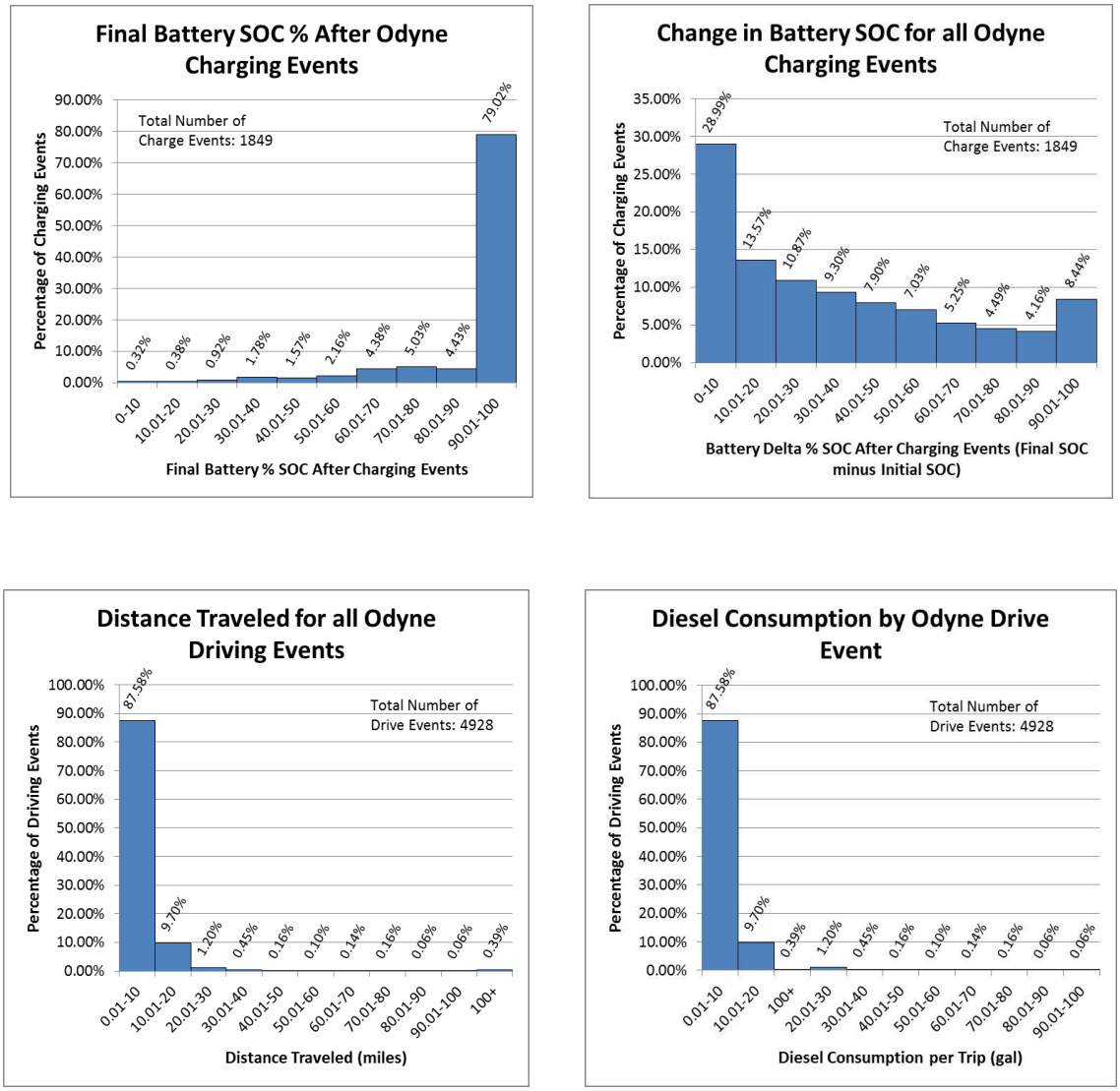

Figure 4.3 - Examples of Data Visualizations in Excel for Decision Support

4.3.7 Recommendations for Future Analysis Work

For future work, here are some additional suggestions that could possibly be used to improve the data analysis methodology outlined here in Section 4 of this thesis. These suggestions were not widely implemented in this study, but are instead seen as logical next steps to build on the methods presented in this section.

1) As datasets grow larger, it will become more important to parallelize the data analysis algorithm and run it on a computer cluster or multi-core machine. For this study, some very initial preliminary work was done in the area of code parallelization, but it was found that the same results could be produced with less software development work and hardware investment by just letting the machines run for longer. However, if the data size grew by another order of magnitude or if tighter deadline ruled out multi-day run times, parallel computing would have a much larger payoff and should be considered.
2) More of the available CAN-communication bus signals could be integrated into the utility factor calculation to develop additional alternate utility factor calculations. For example, since both electric charging energy and fuel injection rate are available, the ratio of electric energy to gasoline used could be used as an alternative measure of utility factor.

4.4 Application of Summarized Dataset and Results

Once the raw dataset is transformed into summarized event data, it is very easy to generate useful numbers and additional analysis to support decisions related to policy, fleet operation, and vehicle design. For example, this study generated utility factor curves from the summarized event data for the fleet of trucks, which supports both policy and vehicle design decisions [2, 41]. Utility factor (UF) curves for PHEV Medium-Duty Work trucks have also never been published, so the results from Odyne are immediately useful. Then, to better understand how the number of daily charging events could affect utility factor, some additional statistics about the charging events were compiled. The charging event statistics support

operator feedback and public policy by indicating that utility factor could be improved if the vehicles could be frequently recharged during the day [2, 41, 53, and 55].

4.4.1 Utility Factor Curve Discussion

This section describes and presents the calculation of utility factor (UF) results for both the Odyne and Via fleets. There are three curves on these graphs. The first curve is the standard utility factor curve in the SAE J2841 specification that was based on NHTS (National Household Travel Survey) data [60]. The second curve is the truck UF curve, calculated using the SAE J2841 methodology [60]. The third curve was calculated using the truck data, but with the SOC-based correction factor added to the standard SAE J2841 methodology to account for the possibility of more than one charge per day. It should be noted that the standard SAE J2841 methodology assumes that vehicles are fully recharged only once every day, which may or may not be an accurate assumption [41, 49, 55, and 60]. Previous work by others has explored alternate utility factor definitions [41, 55].

The drive event summary data table information from the primary analysis described in the previous Subsection 4.3 is then used to calculate the UF curves for the medium-duty truck data. First, each individual vehicle is identified, so UF vs. Range Charge-Depleting (RCD) can be calculated individually for each vehicle. Then, a fleet wide UF curve is fit over this data.

The total driving duration, distance, fuel use, electric energy use, and delta SOC is extracted and compiled for each individual vehicle day. Total vehicle day driving distance is then computed by adding together the driving distance of each individual driving event. Total Daily Delta SOC is calculated by adding together the Delta SOC for blended and CD driving modes.

To build the utility factor curve, a vector of theoretical Range Charge-Depleting (RCD) values is constructed from 0 to 300 miles, in increments of 0.5 miles. This and vehicle daily total driving distance are then used to calculate a utility factor curve for each individual vehicle. The following equation specified in SAE J2841 for the Fleet Utility Factor (FUF) [60] is used for this calculation:

$$UF(R_{CD}) = \frac{\sum_{d_k \in S} \min(d_k, R_{CD})}{\sum_{d_k \in S} d_k} \quad (1)$$

In this equation, the Utility Factor (UF) is a function of the theoretical charge-depleting range (RCD). dk is the daily driving distance of a single vehicle and S is the set of all daily vehicle driving distance data.

Known sources of potential error in the standard SAE J2841 Fleet Utility Factor calculation shown above are the assumptions that it is based on [55]. According to the SAE J2841 Specification [60], there are two main assumptions that go into this calculation:

1) The vehicle starts the day from a routinely achieved, fully charged state.
2) The vehicle is charged to said state before every day of vehicle travel.

Based on these assumptions, the vehicle is only charged once per day. However, in the real world, many PHEV vehicles are recharged multiple times, especially if there is a charging station available at work or if the vehicle returns home multiple times throughout the day. These multiple charges increase the effective utility factor of the vehicle.

An attempt was made to account for multiple charges per day by using the SOC signal to calculate a modified SOC based utility factor. The below equations are used to calculate the modified SOC based utility factor curve. These equations are a slight modification to the standard SAE J2841 Fleet Utility Factor (FUF) equation:

$$UF(R_{CD}) = \frac{\sum_{d_k \in S} \min(d_k, R_{CD} \cdot C_k)}{\sum_{d_k \in S} d_k} \quad (2)$$

$$C_k = \frac{\max(|\Delta SOC_k|, 100 - SOC_{Cutoff})}{100 - SOC_{Cutoff}} \quad (3)$$

In the SOC-based utility factor curve equation, C_k is a factor that increases the effective R_{CD} in the SAE J2841 Fleet Utility Factor equation, based on the total daily change in battery State of Charge, ΔSOC_k. To calculate ΔSOC_k, the changes in state of charge values for every vehicle trip in a day are added together. Note that the absolute value of ΔSOC_k is taken to ensure that the value is always positive. The term 100 - SOC_{Cutoff} represents the percent SOC change that would occur during one fully charge-depleting trip. The SOC_{Cutoff} value represents the battery state of charge level in which the vehicle transitions from a charge-depleting to a charge-sustaining mode, and in this analysis the value was set to 5% for Odyne and 22% for Via (as mentioned previously in Subsection 4.3.3) [15]. Note that the SOC_{Cutoff} value depends on the specific model of vehicle and its hybrid control system architecture. The idea behind the C_k factor is that if a vehicle recharges during the day in between trips, its ΔSOC_k will be greater than its 100 - SOC_{Cutoff}, thus increasing the true charge-depleting range of the vehicle for the day. If ΔSOC_k is less than 100 - SOC_{Cutoff}, the utility factor equation for the day will be the same as the SAE J2841 utility factor. It should also be noted that if the vehicles are not charged at least once per day, the SOC-corrected utility factor equation will output the exact same curve as the standard SAE J2841 methodology.

Below in Figures 4.4 and 4.5 are the two graphs that summarize the utility factor curves for both the Odyne and Via fleets:

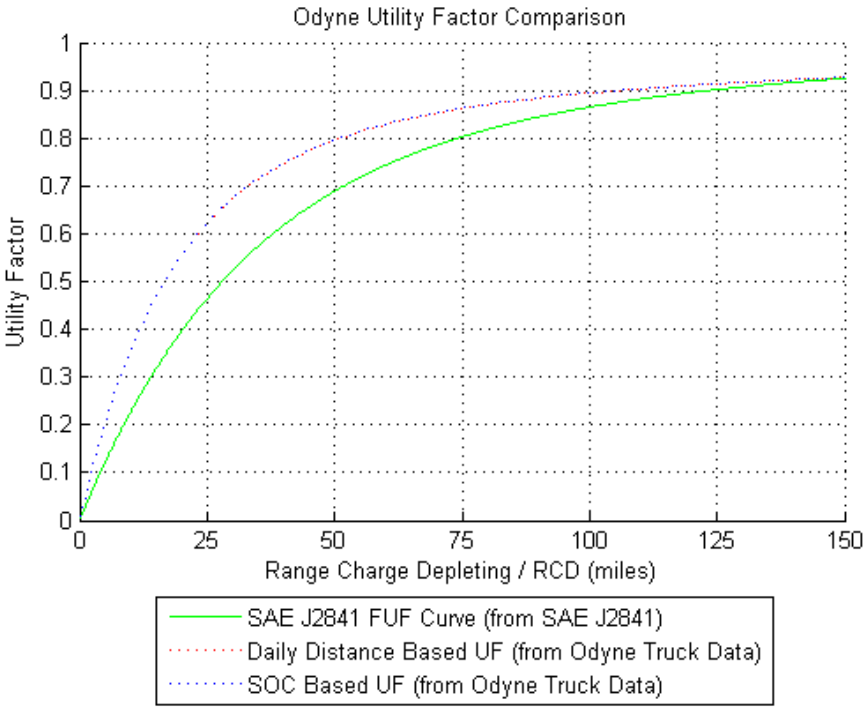

Figure 4.4 - Odyne Utility Factor Curves

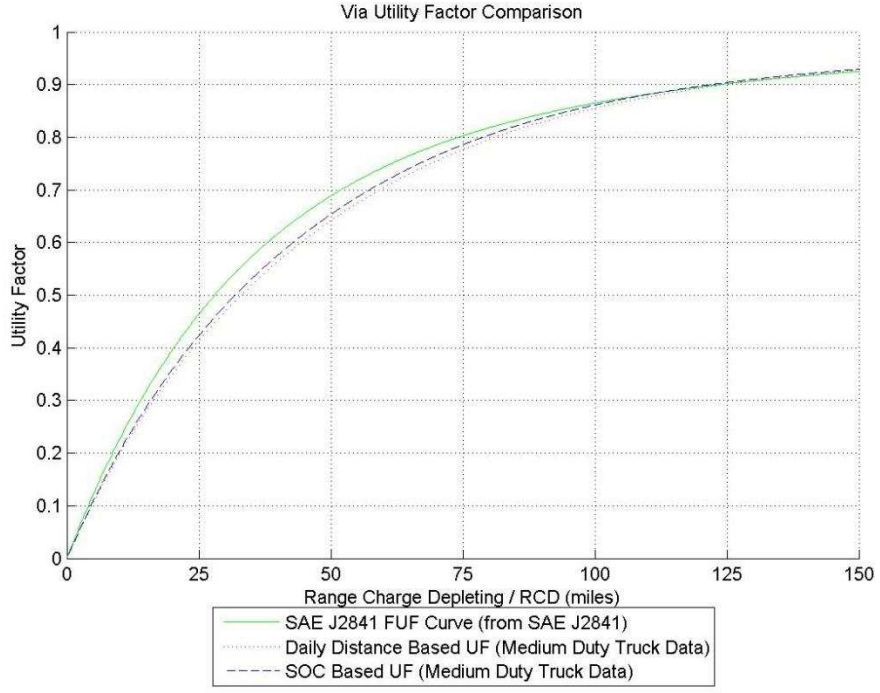

Figure 4.5 - Via Utility Factor Curves

For the medium-duty Odyne trucks, it can be seen that the UF is higher than the standard SAE J2841 UF curve. From a design perspective, this means that these trucks can be designed with a smaller battery than otherwise would be needed if the standard SAE J2841 UF curve was used to meet performance requirements. From a policy perspective, medium-duty trucks may not need as strict of emissions requirements as other commuter vehicles, as they are inherently driven in such a way that increases UF. The SAE J2841 UF curve is just an average of all vehicles in the US, whereas smaller subfleets within the set of all vehicles may have different usage and UF curves [41, 49]. However, it should also be noted that Odyne trucks do not operate in a true all-EV (electric vehicle) mode until the battery is depleted, which is an assumption of the SAE J2841 methodology [15, 60]. Instead, the Odyne Trucks use a blended CD vehicle mode where some gasoline power is used to extend the range of the electric battery. So in reality, the actual gasoline displacement of the Odyne trucks will be less than the gasoline displacement estimated by these UF curves. The actual gasoline displacement of these vehicles could likely be improved if their control strategy was reprogrammed to have a true-EV mode, or a blended-driving mode that used more electric power than the current driving mode.

For the light-duty Via trucks, it can be seen that the UF is much closer to the standard SAE J2841 UF curve than it is for the Odyne trucks. In this situation, it looks like the SAE J2841 UF curve does a good job of approximating the actual real-world UF of Via trucks. However, there is still a slight difference, so depending on the accuracy needed; the UF curve presented in this paper may still be required. Unlike Odyne, the Via trucks operate in a true-EV mode until the battery is nearly depleted, so the Via UF curves are likely representative of their actual utility grid utilization in the field.

In the Odyne and Via truck UF curves, it is also interesting to see that the SOC correction factor did not make a significant difference in the UF curve, so in this situation the standard SAE J2841 assumption of only one charge per day appears to be very reasonable. It is possible that the vehicles are only being charged once per day in line with the SAE J2841 standards, and if the charging pattern of the fleet changed, there could be a significant difference between the two UF methodologies. To better understand the story of why these two curves are so similar, charging event statistics are discussed next in Subsection 4.4.2 to verify this hypothesis.

Overall, the truck UF curves show that light- and medium-duty commercial PHEV's are a great application for PHEV's. The fact that their utility factor curves are equivalent to or higher than the standard SAE J2841 curve means that on average, light- and medium-duty truck PHEV's can displace at least as much if not more gasoline than privately owned commuter PHEV's. Displacing gasoline with electric power can create many positive economic and environmental benefits [2].

4.4.2 Charging Summary Statistics Discussion

Some additional charging event summary statistics were generated to better understand the truck UF curves presented in the previous Subsection 4.4.1. Table 4.1 below presents these numbers for both Odyne and Via:

Table 4.1 - Charging Event Summary Statistics for Odyne and Via

	Odyne	**Via**
Total number of vehicle driving days	1279	1679
Total number of charging events	1850	1076
Average number of charging events per vehicle driving day	1.45	0.64
Mean percent change in battery SOC for charging events	35.0	54.4
Median percent change in battery SOC for charging events	26.5	62.0
Average percent change in battery SOC for all charging events per vehicle driving day (%)	50.7	34.8
Mean final battery SOC after charging event (%)	91.8	90.9
Median final battery SOC after charging event (%)	100.0	100.0

Most charging events almost completely refill the battery, as can be seen in the demonstration graphs presented previously in the *Decision Support Tools Development* Subsection 4.3.6. If a large number of charging events did not completely refill the battery, the SAE J2841 UF curve assumptions may not be accurate.

Combined, these charging event statistics show that in general the fleet is being recharged along the lines of the SAE J2841 assumption of only one fully replenishing battery charge per day. This explains why the two different utility factor curve methodologies presented in the previous Subsection 4.4.1 have such similar results. It is also notable that on average, the Via fleet is not being fully recharged after every day of driving. This information should alert the Via fleet operators that they can potentially improve their efficiency by recharging the vehicles more often. This recommendation is also noted in EPRI's report [15] on page 4-26, which was reached independently of the CSU results presented in this section of the thesis.

The Odyne fleet is charged more than once per vehicle driving day, but analysis showed that a large number of charges only replenishing the battery by a very small amount (see the previously presented graphs in the *Decision Support Tools Development* Subsection 4.3.6). Therefore, it is reasonable to conclude that the Odyne vehicles are being plugged in on days when they are not driving and are already mostly charged.

From an operational perspective, there could be a lot of room for utility factor improvement for both the Odyne and Via fleets if multiple charges could be facilitated throughout the day [2, 15, 41, 53, and 55].[1]

4.5 Conclusions for Event Summary Data

The event summary methodologies presented in this chapter may be beneficial to future vehicle tracking projects that require the analysis of high sampling frequency data from on-board tracking sensors. The ability to summarize a large database of second-by-second driving data points into a list of longer-term events is a particularly difficult task, especially when the data collection devices are not 100% reliable. However, when compiled correctly, this event summary list is also very useful. To demonstrate the utility of these event summary statistics, utility factor curves, charging summary statistics, and demonstration histograms were presented.

This work is also novel because it is the first time that UF curves have been published for a fleet of medium-duty PHEV trucks. The presented UF charts for Odyne provide

[1] All of the charging statistics presented in this section were calculated from the summarized event data using about 80 lines of MATLAB code (including whitespace and comments) which ran on a single core in a matter of seconds. The same analysis could have also been performed in Microsoft Excel. For comparison, the MATLAB code written to create the event summary from the raw second-by-second driving CSV data was thousands of lines of code, and took multiple days to run on a single core. Maintaining summarized event data can greatly simplify, streamline, and expedite the data analysis process when new questions of research, design, operation, or policy are posed.

additional evidence that different policies may be needed to govern different vehicle classes and that a single overarching UF curve for every situation may not be appropriate [41].

The truck UF curves also show that light- and medium-duty trucks are an effective application for PHEV technology, as light and medium-duty PHEV's displace a large amount of gasoline with electric power. These PHEV's can displace at least as much gasoline as privately owned commuter PHEV's, if not more.

SECTION 5

CALCULATING VEHICLE EFFICIENCY AND CORRELATING IT TO OTHER SIGNALS – METHODS AND RESULTS

5.1 Summary of Work

The work presented in this section originated from a class group project in my CS435 Big Data class where I learned how to use Java, Hadoop, and MapReduce to perform big data analysis. The goal of this work was to use the EPRI Odyne and Via truck data described previously to correlate vehicle efficiency to other signals and metrics. Some of the MATLAB code that was used in this section (specifically Subsection 5.2) was similar to the code developed for earlier work. The data management framework was improved from the original framework described in Section 2 by myself and Mike Reid. Mike did the majority of the restructuring.

The algorithm to analyze the data in this section was broken up into three consecutive phases and code was developed independently for each phase. Each phase outputs a new dataset that is the input data for the next data processing phase. The below flowchart in Figure 5.1 summarizes all of the high-level software phases that were created to perform the data analysis presented in this chapter. Then, additional description for each step is provided below the chart.

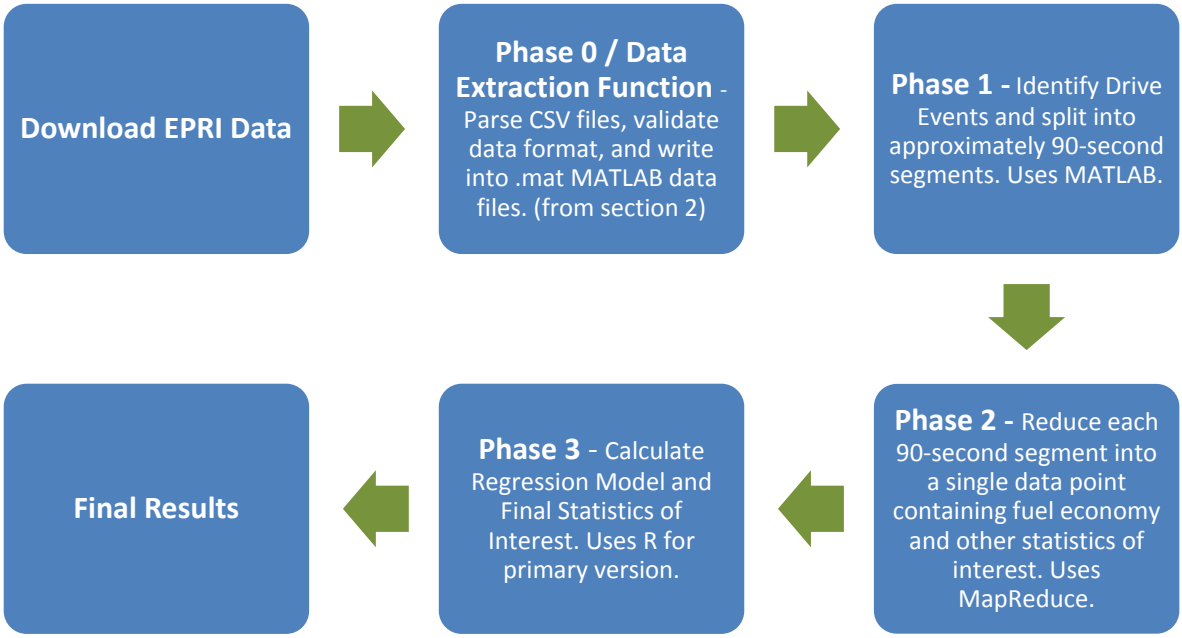

Figure 5.1 - High-Level Summary of the Fuel Economy Correlation Software

Phase 1 of 3 involves cleaning and filtering the raw data, identifying charge-depleting drive events based on the algorithm explained in Section 4, and then splitting each charge-depleting drive event into approximately 90-second drive intervals. The drive intervals are approximate, because it is impossible to always divide any given length of driving time into perfect 90-second intervals. Therefore, each drive event is divided into the number of segments that would make the length of each division as close to 90 seconds as possible. The raw second-by-second data for each of these 90-second drive segments is then written into a CSV file with data from only that drive segment. These CSV files are used as the input to Phase 2 of 3 which was written in Java for the Hadoop MapReduce framework. The idea is that the fuel economy and other metrics can be calculated for each 90-second drive segment to

reduce each of these segments into a single data point. This discretizes the continuous data in a way such that a regression model can be calculated. It was also important to break up the raw data files into smaller chunks to avoid heap space errors in the Phase 2 MapReduce framework, which uses a whole file input format.

The Phase 1 of 3 script is written in MATLAB and is similar to previous data processing scripts. Phase 1 of 3 reads in the raw data from .mat files produced by the Data Extraction Function described in Section 2. A slightly modified version of the Data Extraction Function described in Section 2 was also created for a new data format provided by EPRI and it was informally called Phase 0 of 3 since it came before Phase 1. However, the basic principle and design behind this new Phase 0 is fundamentally the same besides compatibility for the new data format. Phase 0 simply parses raw CSV files, verifies the CSV file format, and writes out the data into .mat files. It should also be noted that parallel processing was not implemented in the Phase 1 MATLAB code so it takes about a full day to process any of the available datasets on a single core. More details about exactly how Phase 1 is implemented are provided in Subsection 5.2.

Phase 2 of 3 is a MapReduce function written in Java. This MapReduce function was run on a Linux computer cluster in the Computer Science department here at CSU. The goal of Phase 2 is to read in each of the CSV files created by Phase 1 that represent about 90-seconds of drive data and reduce each file into a single line of data. The Phase 2 output contains information about the fuel economy, ambient temperature, kinetic intensity, whether the AC was on, etc. Only a mapper in the MapReduce framework is needed to perform this reduction. Since this code can run in parallel and is scalable to large computer clusters, this analysis only

takes about an hour to run on a Hadoop computer cluster with 15-20 machines. More details about exactly how Phase 2 is implemented are provided in Subsection 5.3.

Phase 3 of 3 is where the regression model, visualizations, and any final filtering steps are implemented. The input to Phase 3 is a single CSV file produced from the output to Phase 2. Graphs and regressions can then be created based on the raw data. A few different Phase 3 implementations were created. The first Phase 3 implementation uses MATLAB to plot the vehicle efficiency against other variables, such as ambient temperature, kinetic intensity, cabin temperature, etc. The second Phase 3 implementation is written in MapReduce and performs a linear-regression model with k-fold validation. The advantage of the MapReduce implementation is that it is scalable to much larger datasets, but the disadvantage is that much of the regression calculation has to be programmed from scratch using linear algebra so the regression model could be calculated in pieces running on parallel computers. The third implementation of Phase 3 was written in R and this is likely the best implementation of Phase 3. The R implementation is similar to the MATLAB implementation, except that R provides better statistical tools to calculate confidence intervals on the regression line and other statistics of interest. Other function shapes besides a linear model were also experimented with in R and these produced slightly better results. More details about exactly how Phase 3 is implemented are provided in Subsection 5.4 and sample results are provided in Subsection 5.5.

I would like to thank Joseph Minicucci and Mike Reid for helping me write the software to implement the algorithms that I developed to perform this analysis. A large amount of software development was required to produce these results and I would not have had time to do everything myself. This was a very large project and it would not have been possible without a group effort.

5.2 Details of Phase 1 Analysis Implementation – Data Cleaning, Filtering, and Splitting

This subsection is divided into two additional lower-level subsections. The first subsection (5.2.1) details the data filtering and processing algorithm that was implemented in the Phase 1 analysis software. The second subsection (5.2.2) presents and reviews some of the data validation tools that were developed to provide more information about the impact of each data processing step in the Phase 1 implementation.

5.2.1 Details of the Phase 1 Analysis Algorithm

The Phase 1 script was written in MATLAB and can operate on four different datasets. Both the Odyne and Via platforms have an old dataset and a new dataset. However, only the old Odyne dataset is used for most of the results presented later in Subsections 5.5 and 5.6. A small portion of the presented results used the new Via dataset as well.

Like the *Analyze_all_data* function described in Subsection 2.3, controlling variables are defined at the beginning of the script. The user also has the option to toggle diagnostic plots on and off. If the data is organized in subdirectories, the user has the option to define the subdirectory folder names. It was a lot easier to just hard code the subdirectory names for this application than program MATLAB to search through all of the file folders.

The script will loop through each individual .mat data file and process each of the files separately. These .mat data files are created from the raw CSV files using the Phase 0 / Data Extraction Script which is not discussed here. See Subsection 2.2 for more information about the data parsing and extraction process used to create the .mat files. If the raw data file does not have at least 1000 data points when all of the different signals are counted together, the file

will be skipped. Each raw data file should contain data from one vehicle for one month, or if the data size for one vehicle month is too large then the Phase 0 / Data Extraction Script could have produced multiple .mat data files for one vehicle month. Then, each raw CAN-communication bus signal is parsed from the raw data format so that the data points from each signal can be saved into a separate vector. The script produces an error if there were no data points for a signal name.

In the new data formats for Odyne and Via which are not extensively used in the presented analysis results, each raw signal needs to be sorted by timestamp to ensure that all of the data points are in a sequential order. In the new data, most timestamps are ordered sequentially in local groupings, but these local groupings are also not arranged sequentially. This might be a result of the Hadoop system used by EPRI's contractor to manage the raw data, as Hadoop software has a tendency to write output data in a random order. Fortunately, in the old datasets used for most of this analysis, the raw data was already pre-sorted.

After each individual CAN signal is sorted, another filter removes data points with values outside of a realistic range of values for that signal. This is also referred to as "Filter 1" in the next Subsection 5.2.2 and Table 5.1 where the impact of each data filter is quantified. The exact values of the realistic range are just determined by using basic engineering judgement and common sense. There is no formula used to derive these values. For example, an ambient temperature of 100 degrees Celsius does not make sense in the real world as we know that the atmosphere is not at boiling temperature. Below are the acceptable value ranges that were chosen to filter each signal in the dataset. Data points outside of these ranges are deleted.

- Ambient Temperature: [-30, 50] deg C
- Battery Voltage: [0, 600] Volts
- Battery Current: [-400, 400] Amps
- Battery State of Charge (SOC): [0, 100] Percent
- Vehicle Speed: [0, 200] kph
- Odometer: [0, 500000] miles
- Cabin Temperature: [-30, 50] deg C

After the range of each signal is checked, the next step is to count the number of data points in each signal in the data file. If any of the above signals have less than 100 data points in a data file, the data file will be skipped. This is also referred to as "Filter 2" in the next Subsection 5.2.2 and Table 5.1.

Next the data is run through a filter to remove duplicate timestamps. This is also referred to as "Filter 3" in the next Subsection 5.2.2 and Table 5.1. There is an uncommon glitch in the data where a sensor will report two different values for the same timestamp and this causes execution problems later in the software if the duplicate timestamps are not removed.

Again, the length of every signal in the data file is checked after the duplicate time stamp filter to see if the filter reduced the data size below the required threshold of 100 data points per signal. In this case, no additional data files were removed, but it is good to check one final time after any filter that removes data because it is always possible that a data file will be made too short. This is also referred to as "Filter 4" in the next Subsection 5.2.2 and Table 5.1.

After duplicate timestamps are removed, all of the CAN signals are then interpolated onto the speed timestamp values. The vehicle speed timestamps were chosen to be the projection target because these data points are generally recorded when the vehicle is driving. This aligns the asynchronous data collection from multiple sensors onto the same set of timestamps so different signals can be compared directly using the same timestamp values. This is very similar to the process used and described previously in Subsection 4.3.3.

Then, the drive event identification algorithm previously explained in Section 4 is used to identify where charge-depleting drive events occurred with some adjustments to the algorithm parameters. Here are the parameters that were used to tune the performance of the algorithm from Subsection 4.3.3 for this situation:

- Minimum Speed to Identify Drive Event = 0.01 kph
- Minimum SOC for Charge-Depleting mode = 6 % (Odyne)
- Minimum Allowable Drive Event Duration = 90 secs
- Minimum Allowable Time Gap Between Drive Events = 30 secs
- Minimum Number of Data Points Allowed in an Event = 20

In addition, to simplify the analysis, charge-depleting and charge-sustaining modes are not redefined based on additional available information for each drive event such as the change in SOC and the fuel injection rate, as explained in Subsection 4.3.3. This is a difference between the analysis methodologies presented in Subsection 4.3.3. In this analysis, the blended driving mode of the Odyne trucks is considered to be a charge-depleting mode and is referred to as such in this section.

Once each charge-depleting drive event is identified, the algorithm splits up each drive events into approximately 90-second drive segments that can later be reduced into single data points in a regression model. The goal is to discretize continuous data. For this discussion, a drive event is defined as the data from when the vehicle started driving to when it stopped driving (while ignoring short, brief stops by the vehicle). A drive segment is defined as an approximately 90-second interval of data within a drive event.

The length of each drive segment varies depending on the length of each drive event as it is normally not possible to divide a drive event up into perfect 90-second intervals. It was decided that it is better to have slightly uneven drive segment times than drive segments with large amounts of non-driving time beyond the end of the drive event. Including a large amount of non-driving time in a drive segment would essentially amount to a very short drive segment and give unequal weighting to that short time period at the end of the drive event in the regression model.

To check that the data interpolation is working properly across the drive segments and events, the software counts the number of pre-interpolation data points for each CAN signal after "Filter 4" that are contained within the drive interval. This is to see if the interpolated estimations for each CAN signal are based on nearby data points of actual recorded data for that signal. This is one improvement over the analysis methodology presented in Subsection 4.3.3. If a drive event or segment does not contain any actual pre-interpolation data points, the interpolation over that drive event or segment is not going to be accurate.

Any drive event that does not have at least one actual data point for ambient temperature, AC switch state (on/ off), heater switch state (on/off), or cabin temperature is ignored and output for that event is suppressed. These are referred to as the "long-term

signals." Any drive segment within a drive event that does not have at least 20 data points for engine fuel injection rate, battery voltage, battery current, and battery state of charge is ignored and output for that event is suppressed. These are referred to as the "short-term signals." These two categories of checking the entire drive event vs. the drive segment are based on how quickly the signal values generally change and are recorded by the data collection system. Signals such as the ambient temperature and whether the heater is on or off tend to be longer-term signals that are generally more stable over longer periods of time, so their values can be more safely extrapolated across the larger time range of an entire drive event. The other signals change more rapidly and must have data points recorded in each individual drive segment. Note that not all versions of the data and vehicle models record all of these signals, so if a platform does not have all of the mentioned signals in the raw data, the software only checks for the signals that are available and the final data analysis is adjusted accordingly.

If a drive segment of approximately 90 seconds of length has all of the required drive signals during the data interpolation check, the different signals are compiled and written out into a unique CSV file that only contains data from that drive segment. In this CSV file each CAN-communication signal is placed into a separate column and the timestamp values are used as the row labels. Each CSV file should have approximately 90 rows of data. A unique key that can be used as a key in the MapReduce Framework is also generated for each drive segment. The key contains unique identifying information for each drive segment in a text string so the individual drive segments can be kept separate if needed.

This completes the description of the Phase 1 data processing algorithm. After the CSV files are written out by this process, they need to be uploaded onto a Hadoop Cluster (which uses the HDFS file system) so they can be processed by the Phase 2 MapReduce function.

Section 5.2.2 provides a description of some of the data validation tools that were built into the MATLAB Phase 1 software and provides an initial quantitative assessment of the impact from the data filtering steps described in this section.

5.2.2 Review of the Validation Tools That Were Built Into the Phase 1 Process and What They Reveal About Data Filtering

During the MATLAB Phase 1 process, a number of validation tools were built into the software to verify that each data processing and filtering step was working correctly. The goal was to produce some diagnostic output for the intermediate data processing steps to better understand how those steps were impacting the real-world data in practice. This helped prevent the software from becoming a "black-box" algorithm where only input and output data would be accessible and the inner workings of the software would be obscured.

For example, a number of graphs can be generated for each data file to visually verify that the process is working correctly. A graph of speed vs. time for each drive event is produced and vertical-red lines indicate where the drive event is being split into the approximately 90-second drive segments. An example of one of these graphs is shown in Figure 5.2. Note that the timestamps on the x-axis are in a MATLAB serial date format. This tool was very helpful to debug the software and it helped identify problems in the first versions of the software where the start and end timestamps for each drive event did not line up with the actual data.

By looking through the collection of these graphs it is easy to visually identify where drive segments are not being appropriately identified or divided. Since there are a large number of data files, it was not practical to have a human examine every single graph.

However, as a collection, it is easy to flip through a few hundred of these graphs in the Windows Photo Viewer to identify common problems that affect a large number of data files. In addition, if an individual data file produces an error, these graphs provide a specific source of information that can be referenced for any individual data file if needed.

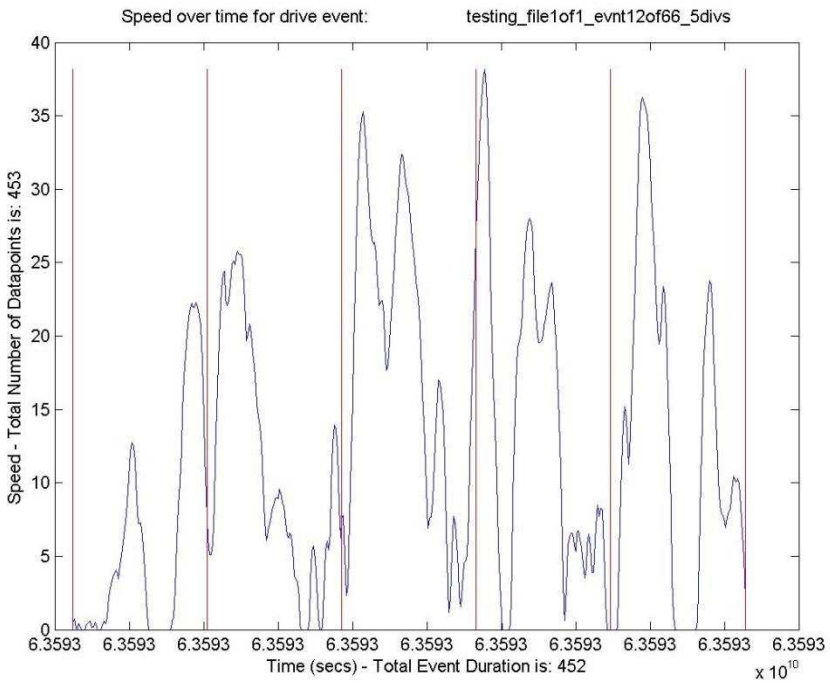

Figure 5.2 - Speed vs. Time Graph Showing Drive Segment Divisions for a Drive Event

In addition, for each data file, graphs are made of each individual raw CAN-communication signal vs. time to get an understanding of how the data is structured. These are helpful to identify CAN-communication signals that may have bad raw data. As discussed for the previous example presented in Figure 5.2, a large number of these graph data files were generated since there are a large number of raw data files. Figures 5.3 and 5.4 below show examples of what some of these raw CAN signals look like. Note that some information on these graphs has been "whited out" to protect driver privacy and anonymize the data.

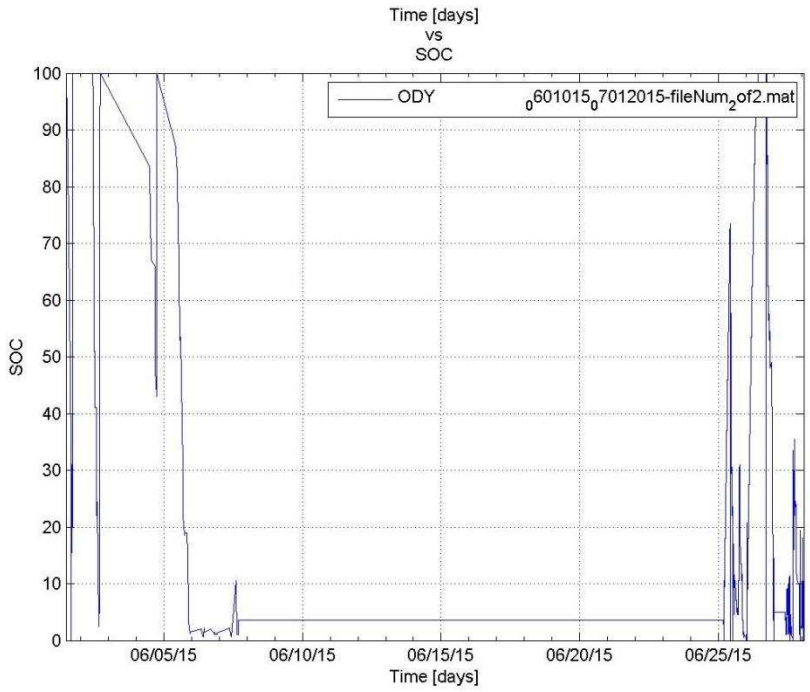

Figure 5.3 – Battery SOC Signal (in %) vs. Time

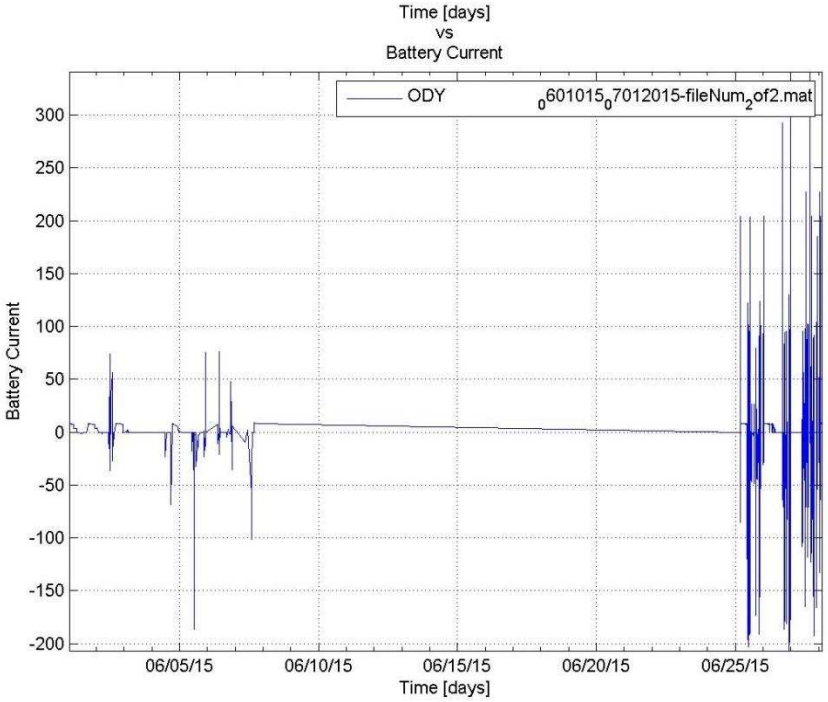

Figure 5.4 - Current from the Main Vehicle Battery (Amps) vs. Time

A number of additional graphs that plot multiple signals on top of each other are also produced by the software to see how the different sensor signals align before the data interpolation step. These graphs help to better understand how the data is being interpolated during the data interpolation step. See Figures 5.5 and 5.6 below for examples of these graphs. The point of this diagnostic tool is to overlay all of the signals that are needed to analyze drive events when vehicle speed data points are being recorded. It can be seen that most of the raw signals that are used in the drive event data analysis are only recorded when the vehicle speed is greater than zero. In this graph, the red points are vehicle speed, the green points are AC switch state, the cyan points are ambient temperature, the magenta points are cabin temperature, and the dark blue data points are heater switch states. Note that some of the signals have been multiplied by a constant so the different signals all scale to a similar size when they are superimposed onto the same graph. The purpose of these graphs is not to see the true quantitative values of the signals. It is to see when the data points are being recorded relative to the other signals.

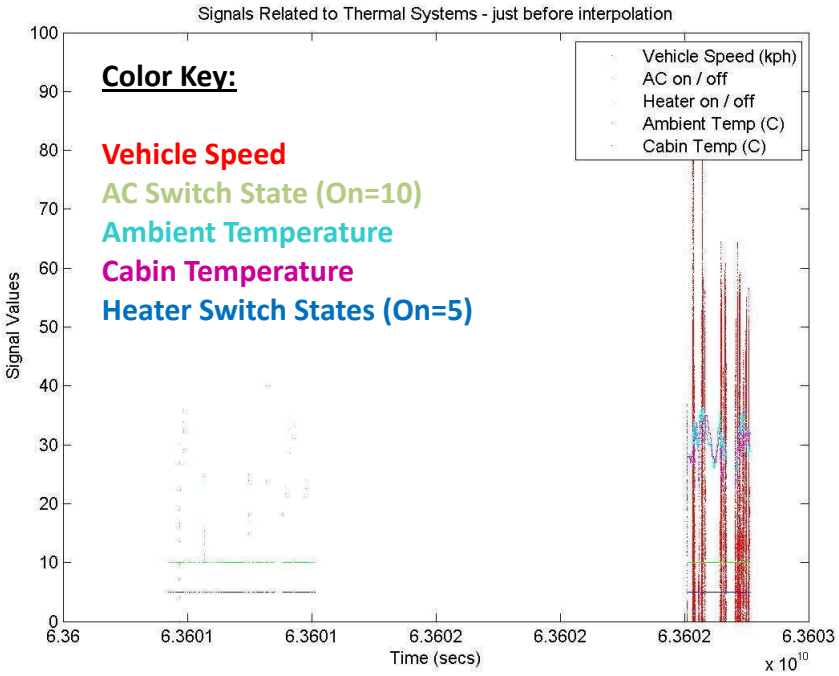

Figure 5.5 - Thermal Systems Signals

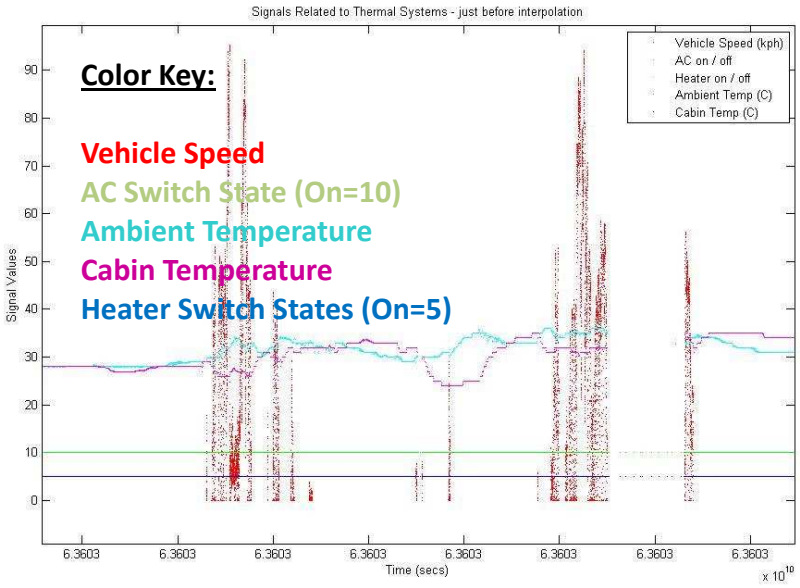

Figure 5.6 - Thermal Systems Signals (Zoomed in)

Finally, in addition to the visual graphs that are generated by the software to aid in the debugging process, the data analysis script contains counter variables to track how many data points, data files, drive events, and approximately 90-second drive segments remained after the different data-filtration steps. This provides information about the actual impact these data filtering steps have when applied to the real-world vehicle data. The final counter values after all of the Odyne data was processed are presented in the following three tables (Tables 5.1, 5.2, and 5.3) and one figure (Figure 5.7).

Table 5.1 shows the number of data points remaining for each individual CAN signal before those data points are projected onto the same time stamp values in the data interpolation step. Note that data is asynchronous and each unique CAN signal has a different number of data points. Table 5.2 shows the number of raw data files that were loaded initially and the number of data files that had enough signals to actually be used for the analysis. Table 5.3 summarizes the data filtering steps after all of the CAN signals are interpolated onto the same set of timestamp values.

Table 5.1 – Number of Data Points Remaining After Each Individual Data Filtering Step Before the Time Stamp Interpolation

	Data Filtration Steps				
CAN Signals used in Analysis	**RAW -** Number of Data points for each specific signal in all raw data files before any data filtering	**FILTER 1 -** Number of data points after Filter 1, which checks that each data point falls within an acceptable range for the signal and remove outliers	**FILTER 2 -** Number of data points after Filter 2, which removes any data files where any CAN signal in that file has less than the required number of data points after Filter 1	**FILTER 3 -** Number of data points after Filter 3, which removes Duplicate Time Stamps	**FILTER 4 -** Number of data points after Filter 4, which removes any data files where any CAN signal in that file has less than the required number of data points after Filter 1
AC	19120068	N/A	11682104	11519643	11519643
Heat	19118643	N/A	11681989	11519512	11519512
Fuel Injection Rate	35236325	35236325	26823526	26349674	26349674
Ambient Temperature	7143466	7142968	4436786	4368418	4368418
Battery Voltage	216268335	216268335	133843107	131597486	131597486
Battery Current	216268374	216228533	133843020	131597423	131597423
Odometer	10213277	10211332	8770931	8585474	8585474
SOC	80218917	80218917	52429475	51117262	51117262
Speed	5525692	5525692	5383072	5247686	5247686
Cabin Temperature	7143466	7130675	4428884	4360654	4360654
Total Data Points from All Signals	**616256563**	**616201488**	**393322894**	**386263232**	**386263232**

Table 5.2 – Data File Filtering Summary

Data File Filtering Summary	
Total data files loaded initially	753
Total data files fully processed and written out - No processing errors such as too few data points	397

Table 5.3 – Data Filtering Steps After the Linear Interpolation Step

Data Filtering Steps after all CAN signals are interpolated onto the same set of time stamps (listed in sequence of processing order)	
Total number of unique time stamps after interpolation (same as the vehicle speed data point count after Filter 4)	5247686
Total number of Charge Depleating events identified	14391
Total number of Charge Sustaining events identified	2227
Total number of unique time stamps in all identified CD drive events	3864768
Total number of Charge Depleating events that had sufficient pre-interpolation data points between the start and end timestamps for what are defined as "long-term" signals	13708
Total number of approximately 90-second drive segments calculated from all remaining CD events after the previous long-term pre-interpolation data point check	41951
Drive Segment Filter 1 - Total number of approximately 90-second drive segments that contained enough short-term pre-interpolation data points for all short-term signals	39157
Drive Segment Filter 2 - Total number of approximately 90-second drive segments that contained the minimum number of interpolated data points	39157

In addition, the results in Table 5.1 were plotted into a bar chart using MS Excel for easier visualization. See Figure 5.7 below:

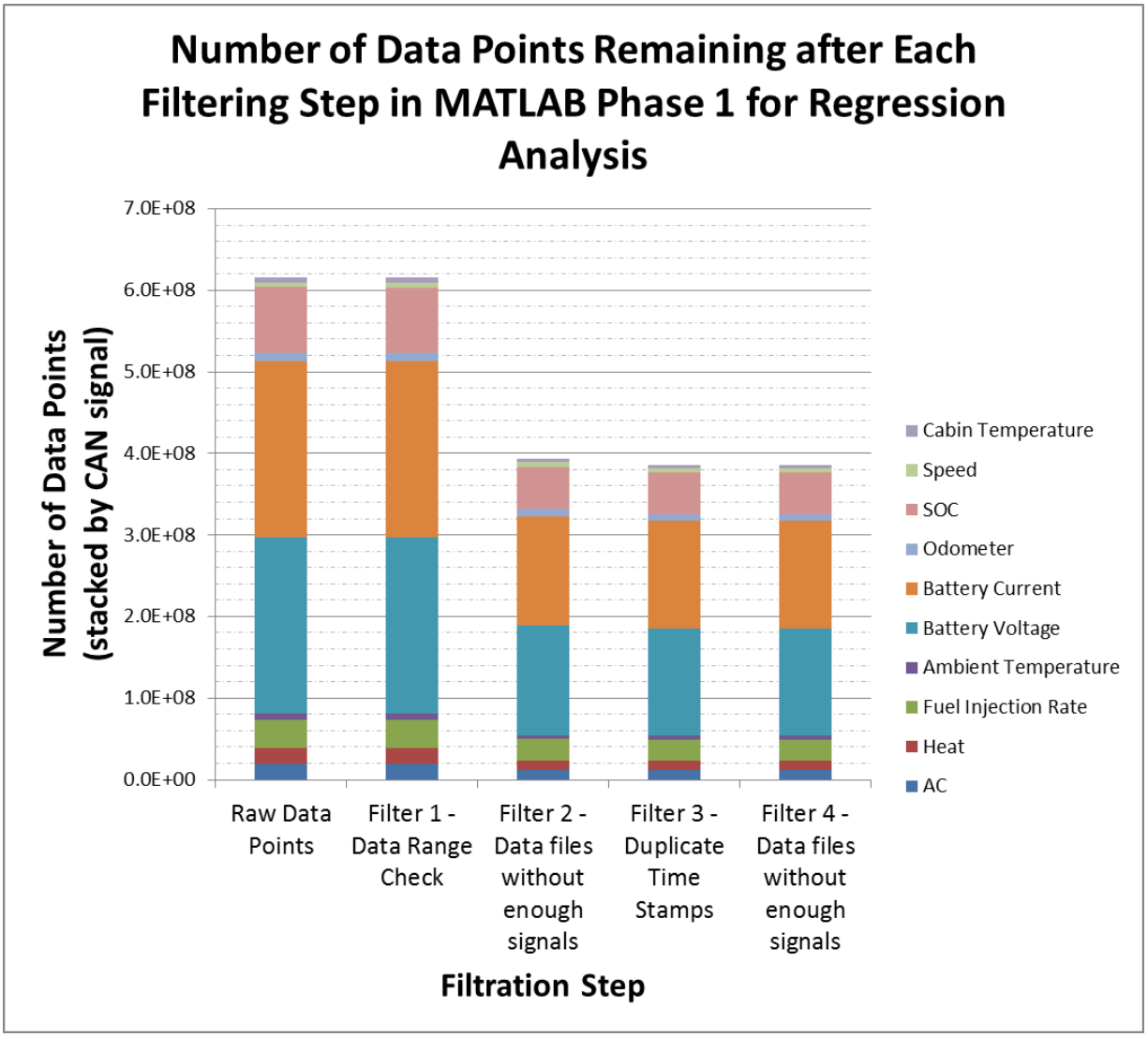

Figure 5.7 – Results Plotted from Table 5.1: Data Points Remaining After Pre-Interpolation Data Filtration Steps

Notable details related to the data presented here in Tables 5.1 - 5.3 and Figure 5.7 are listed below:

- In Table 5.1, the total raw data point count does not include small data files that were initially ignored because they contained less than the minimum required

number of data points, which was 1000 data points for all signals combined. Since these files only have a few data points, leaving them out of the raw data point count at the beginning should not significantly decrease the number of raw data points recorded in the first column of Table 5.1.

- In Table 5.1, note that the AC and Heat signal data point counts under Filter 1 are listed as "N/A." This is because the range filter does not apply to AC and Heat signals since they are discrete on/off values instead of continuous data. For the total number of data points in Table 5.1 and Figure 5.7, the raw AC and Heat data point count is also used as the count after Filter 1.
- In Table 5.2, the total number of data files loaded initially does include the small data files that are immediately ignored because they contained less than the minimum required number of data points, which was 1000 data points from all signals combined.
- Not all of the numbers presented in Table 5.3 are counts of individual data points. This table also includes some statistics about the number of drive events and the drive segments that each event is split into.
- In Table 5.3, the number of charge-sustaining events is only included for reference. Charge-sustaining events are not used in the data analysis process.
- See Section 5.2.1 for more details about each specific step in the data-filtration process and the sequence of data processing and filtering steps.

After reviewing the results of the data-filtration step counters presented above, here are some notable observations:

1) When referencing Figure 5.7, it is surprising that so few vehicle speed data points were collected. This is important because all of the other signals are interpolated onto these timestamps. It is possible that the data collection system could be improved by collecting more of these data points to improve the interpolation accuracy. Unfortunately, it is unlikely that any other CAN signal timestamps could have been used for the interpolation target in this situation. It might be possible to use the fuel injection rate on Odyne, but since these vehicles also have an electric motor that can be used for propulsion, it is possible that in some situations the fuel injector would not be used when the vehicle is driving. The Odometer signal is known to have some faulty data on Via so this might not be the best signal to use for the interpolation projection target either. Some of the electrical signals such as SOC, battery current, and battery voltage are recorded for other truck operation modes in addition to driving, such as Odyne's stationary and charging mode, so these would not be a good choice for the interpolation target either.
2) The raw number of data points removed by each filtration step should not be the only consideration when determining that filter's effectiveness. For example, although Filter 3 in Table 5.1 only removed a small number of data points, the data interpolation step later in the process would have crashed if the software did not filter these duplicate timestamps.
3) Filter 2 removed the largest number of data points when it is compared to the other data-filtration steps. This filter removes entire data files that do not contain the

minimum number of data points for each signal, which in this case is 100 data points. This means that a large number of data files are missing at least one of the required signals listed in Table 5.1 and there could be an opportunity to improve the reliability of the data collection system on Odyne Vehicles. It is unknown why so many signals were missing from the original dataset.

4) Filter 4 in Table 5.1 did not remove any data points. This is because the previous duplicate time stamp filter only removed a small amount of data and no individual CAN signal in any individual data file dropped below the minimum number of required data points after Filter 3. However, it is still a good idea to include Filter 4 in the overall process when analyzing other datasets because it is possible that a few files may still need to be removed when the algorithm is used in other applications.
5) In Table 5.3, it can be seen that checking if each drive event or segment contains enough pre-interpolation data points for each individual signal removes a significant number of drive events and segments. About 5% of the drive events were removed because they did not contain enough long-term signal data points such as the AC on/off CAN signal. Then, once the remaining drive events were split into drive segments, about 7% of those segments were removed because they did not contain enough short-term signal data points such as the battery current CAN signal. It is possible that the removed percentage of data is large enough to have a significant impact on the final results, depending on the level of accuracy desired in the calculation.

5.3 Details of the Phase 2 Analysis Implementation – Reducing Drive Segments Into Single Data Points

For this portion of the analysis the Hadoop MapReduce framework is used and MapReduce functions are written in Java [29, 33]. Hadoop is a Distributed File System (DFS) that runs on a Linux computer cluster and it is commonly known as the Hadoop Distributed File System (HDFS). MapReduce is a data analysis framework that runs on top of Hadoop to efficiently process large amounts of data in parallel. To use MapReduce, one generally writes a mapper function that parses the data files, a reducer function that combines the output of the mapper function, and a main driver function that controls the job parameters and overall execution. Data is organized into key / value pairs where the key is used to group the data and the value represents the actual data values. For this analysis only a mapper function was used and the input was set to a whole file input format that would read in the entire CSV file for each drive segment into a single mapper. The MATLAB code in Phase 1 was used to pre-split the data to avoid heap space errors that can be encountered when using a whole file input format in the mappers.

The algorithm for the Phase 2 process is much simpler than for the Phase 1 process. In Phase 2, a mapper in the MapReduce framework is used to reduce each of the CSV data files that are output from the Phase 1 process into a single data point. The mapper function first parses each CSV file to identify the individual signals. Then, trapezoidal integration is used to calculate fuel consumption, electricity consumption, and total distance traveled using the fuel injection rate, speed, battery voltage, and battery current signals. Battery power is calculated by multiplying the voltage and current signals from the battery and then integrating. Other values, such as ambient temperature, AC on / off (0 or 1 values), and the battery state of charge

are just averaged over the 90-second drive segment to produce a single data point for that drive segment. Kinetic intensity is also calculated during this step to give another value to which the efficiency data could be correlated [46]. Kinetic intensity can be used to measure driver aggressiveness. The goal is to provide a number of different predictor variables that can be correlated against the response vehicle-efficiency variable.

An equivalent vehicle efficiency is then calculated using the electric and fuel efficiency. This is done by using the energy equivalency of diesel fuel. The conversions used are 1 gallon of gasoline = 33.44 kWh [61, 62] and 1 gallon of diesel has 113% the energy density of 1 gallon of gasoline by volume [63].

All of this data is output by the mapper function into individual files that each contained a single line of data. These are then combined into a single CSV file that contains all of the fleet data using Hadoop's getmerge command. Alternatively, a basic reducer function can also be switched on in the main driver class of the MapReduce code to combine the mapper output into any number of data files. It should be noted that MapReduce writes output in a random order so there is no defined sequence in the order of the output data. Once this single CSV file is created for all of the fleet data, it can be analyzed using the Phase 3 code to produce regression results and other statistics of interest.

I would like to give special thanks to Joseph Minicucci for implementing the Phase 2 algorithm into Java code for MapReduce. He did a great job of organizing the code and creating a clean script to execute this algorithm effectively. The results presented later would not have been possible without his implementation.

5.4 Details of the Phase 3 Analysis Implementation – Regression Models

Once the data reaches the Phase 3 analysis software, it is no longer a "big data" problem due to the data reduction and summarization steps in Phases 1 and 2. However, all of the data still resides in a CSV file with about 30,000 lines of data and a process is still needed to interpret this data. Three different frameworks were created to do this. Alternatively, it would also have been possible to analyze the Phase 2 output data using Microsoft Excel, although that option was not pursued for this project.

The first Phase 3 framework is written using MATLAB. It plots all of the data points and creates a number of linear-regression models to check how vehicle efficiency might correlate against other variables. On the Odyne trucks the equivalent fuel economy is compared against ambient temperature, AC switch states, cabin temperature, heater switch states, kinetic intensity, and vehicle calibration. The electric only fuel economy is also compared to ambient temperature. Vehicle calibration is a control state that is programmed into only the Odyne trucks and it is either mild or aggressive. A mild calibration slows down the rate of battery depletion and uses more gasoline during the charge-depleting mode to extend the battery range, while an aggressive calibration does the opposite [15]. Discrete values, such as vehicle calibration, AC on/off, and heater on/off are represented by zero or one values so a regression can be drawn. Drive segments where the switch state transitions from off to on are represented as fractional values that represent the proportion of time that the switch state was on or off. In addition, a few other statistics such as the average fuel economy for both mild and aggressive calibrations are calculated. Finally, extreme outliers are filtered out from the input data for this script before the regression models are calculated. The

description of the Phase 3 R framework later in this subsection has more information about this outlier filtering process.

The second Phase 3 framework was developed for the CS435 Big Data analysis class at CSU and it uses MapReduce to calculate a linear-regression model piecewise. The least squares equation from linear algebra is used in a way that allows regression models to be calculated on subsets of the data. The regression models for the subsets can then be added together in the reducer phase to produce the entire regression model. This framework also performs k-fold testing. For scientific work, this framework is not used to publish results, as the data is not large enough to justify parallel computations and the other single core methods are much simpler, easier to debug, and troubleshoot. K-fold validation is also not used in the presented scientific results in this document.

The third framework developed for the Phase 3 analysis component is similar to the MATLAB framework except that it was developed using the R programming language. In addition, the R framework implements a final data filtering step before the regression was run. For the ambient temperature signal, any Odyne data points outside the range of -10 to 49 degrees C are removed from the regression model. In addition, any equivalent fuel economy data points outside the range of -10 to 50 miles per gallon are removed from the regression model. These outliers are considered beyond the expected realistic range of values for this data. It is not clear why the Phase 1 and 2 software produced these outlier data points, but it is believed that they can be safely removed from the regression model as they only represent about 1% of the data in the old Odyne dataset and do not fall within a realistic range of values. Before this final filtering step on the Odyne dataset, R had 39,153 data points loaded from the Phase 2 CSV output file. After this filtering, 38,761 data points remained. These filters were

then applied to the MATLAB script described previously that can be run as an alternative to the R script. Finally, additional models besides a linear model are fitted to the data, such as a semi-log and quadratic model, to see if a better fit could be achieved.

5.5 Sample Results from the Vehicle Efficiency Correlations

Results from the Phase 3 R script are presented using the old Odyne dataset. There is a new dataset for both Odyne and Via that contains data collected from a wider range of dates, but only a little of the analysis on the new Via dataset is presented in Subsection 5.5.6 and it did not produce meaningful results. The new dataset is required to correlate ambient temperature to vehicle efficiency for Via as the ambient temperature signal is not present in the old Via dataset. Hopefully, future work can present higher quality results based on this new data. The old Odyne dataset was the same dataset that was used for the results in Section 4 so refer to that section for more details about the data used for this analysis.

5.5.1 Vehicle Efficiency vs. Ambient Temperature – Linear and Quadratic Models for Odyne

First, all of the data points from the approximately 90-second drive intervals are plotted on a graph of equivalent fuel economy (mi/gal) vs. ambient temperature (deg C). Both linear and quadratic models are fit to this data. The quadratic model tests if the data has the same trend at both low- and high-ambient temperatures, but results show that the quadratic function is very close to the linear function with a slight curve. The scatterplot with these regressions is presented in Figure 5.8 below:

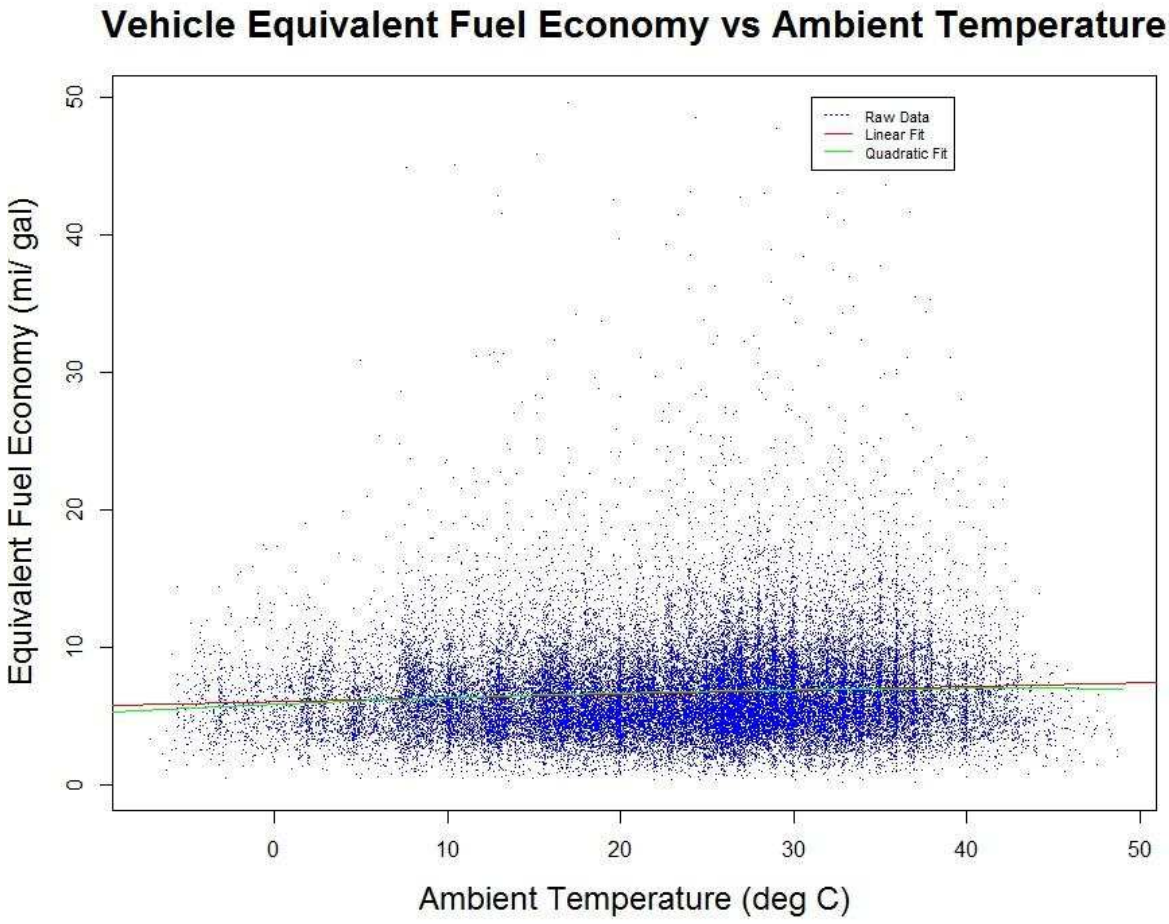

Figure 5.8 - Trend in Equivalent Fuel Economy vs. Ambient Temperature for Odyne Trucks

On the linear model, the p-values for the regression coefficients are less than $2x10^{-16}$ where the null hypothesis is that the true coefficient is equal to zero. On the quadratic model the p-values are higher but still very small. The R-squared values are also small. The linear model has an R-squared of 0.005780 and the quadratic model has an R-squared of 0.006234. Since the p-values on the regression model are small and the R-squared values are low, it can be concluded that the models are poor predictors for any individual data point, but they also do represent the overall average trend seen in the global collection data points. Therefore, this model could be used as an average to represent the overall fleet performance at these different

temperatures, but it could not be used to predict the fuel economy of any individual driver for any individual trip or 90-second drive interval. Below (in Figure 5.9, Figure 5.10, Table 5.4, and Table 5.5) is the console output from R with these results, as well as a table that summarizes key parameters from the console output:

```
> summary(Fit)

Call:
lm(formula = 1/equivalentFuelEconGalPerMile ~ avgAmbientTempInC,
 data = filteredData)

Residuals:
Min      1Q      Median  3Q     Max
-6.925  -2.249  -0.653  1.467  43.013

Coefficients:
                    Estimate  Std. Error  t value  Pr(>|t|)
(Intercept)         6.10060   0.04582     133.13   <2e-16 ***
avgAmbientTempInC   0.02702   0.00180     15.01    <2e-16 ***
---
Signif.  codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 3.541 on 38751 degrees of freedom
Multiple R-squared: 0.00578,        Adjusted R-squared: 0.005755
F-statistic: 225.3 on 1 and 38751 DF, p-value: < 2.2e-16
```

Figure 5.9 - R Code Console Output for the Linear Regression Model

Table 5.4 - Coefficients and Values for the Linear-Regression Model of Vehicle Efficiency vs. Ambient Temperature

Parameter	**Estimated value**	**p-value**
y-intercept	6.10060 (mi/gal)	Less than $2x10^{-16}$
slope	0.02702 (mi/(gal*C))	Less than $2x10^{-16}$
R-squared	0.00578	N/A

```
> summary(Fit2)

Call:
lm(formula = 1/equivalentFuelEconGalPerMile ~ poly(avgAmbientTempInC,
 2, raw = TRUE), data = filteredData)

Residuals:
 Min     1Q      Median  3Q     Max
-6.837  -2.252  -0.651  1.469  42.961

Coefficients:
                                        Estimate    Std. Error  t value  Pr(>|t|)
(Intercept)                             5.8764362   0.0702665   83.631   <2e-16 ***
poly(avgAmbientTempInC, 2, raw = TRUE)1  0.0539407   0.0066461   8.116    4.95e-16 ***
poly(avgAmbientTempInC, 2, raw = TRUE)2  -0.0006267  0.0001489  -4.208    2.59e-05 ***
---
Signif.  codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 3.54 on 38750 degrees of freedom
Multiple R-squared: 0.006234,       Adjusted R-squared: 0.006183
F-statistic: 121.6 on 2 and 38750 DF, p-value: < 2.2e-16
```

Figure 5.10 - R Code Console Output for the Quadratic Regression Model

Table 5.5 - Coefficients and Values for the Quadratic-Regression Model of Vehicle Efficiency vs. Ambient Temperature

Parameter	**Estimated value**	**p-value**
a - intercept	5.8764362 (mi/gal)	Less than $2x10^{-16}$
b – linear term	0.0539407 (mi/(gal*C))	$4.95x10^{-16}$
c – quadratic term	-0.0006267 (mi/(gal*C^2))	$2.59x10^{-5}$
R-squared	0.006234	N/A

Equation is of the form: $y = a + bx + cx^2$ = equivalent fuel economy

Next, a residual and QQ-plot were constructed for the linear model explained above. This is shown below in Figure 5.11. It shows that the data is skewed and not normally distributed.

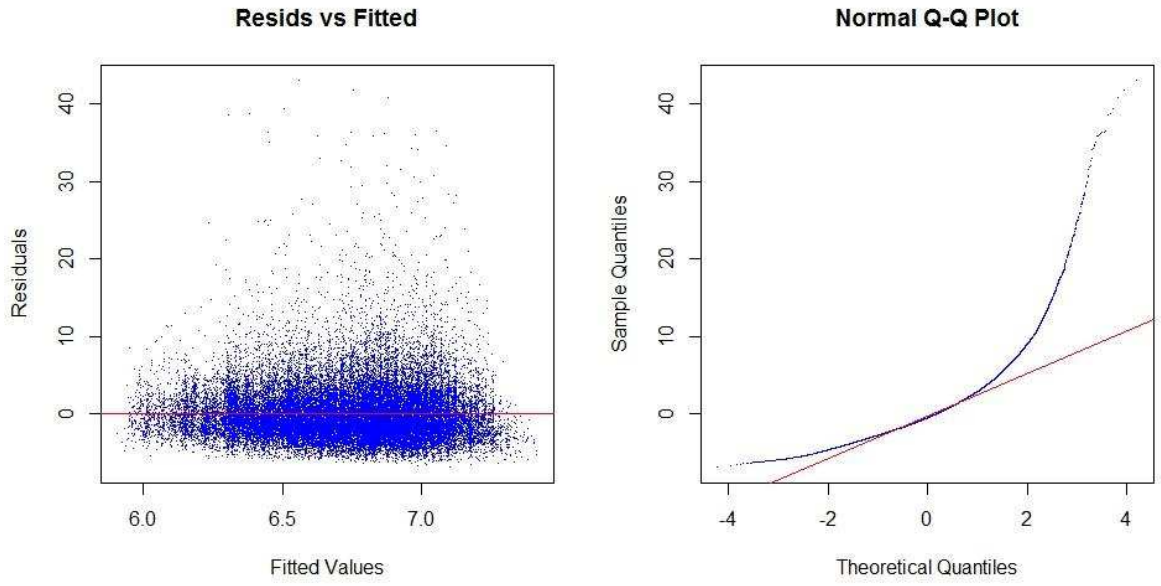

Figure 5.11 - Residual and QQ-Plot for the Linear Model of Ambient Temperature vs. Equivalent Fuel Economy

5.5.2 Vehicle Efficiency vs. Ambient Temperature – Semi-Log Model for Odyne

To correct the problem of skewed and non-normally distributed data in the previous Subsection 5.5.1, the data was replotted on a semi-log scale based on a natural logarithm and the linear-regression model was redrawn. The graphs and table below (Figures 5.12 – 5.14, and Table 5.6) show the new regression, residual plot, and QQ-plot. These graphs show that the semi-log transformation improves the assumptions behind the linear model, but it is still not perfect. The trend of lower fuel economy at higher temperatures remains in the semi-log regression model. It is unclear what kind of regression model would create a near-perfect QQ-plot.

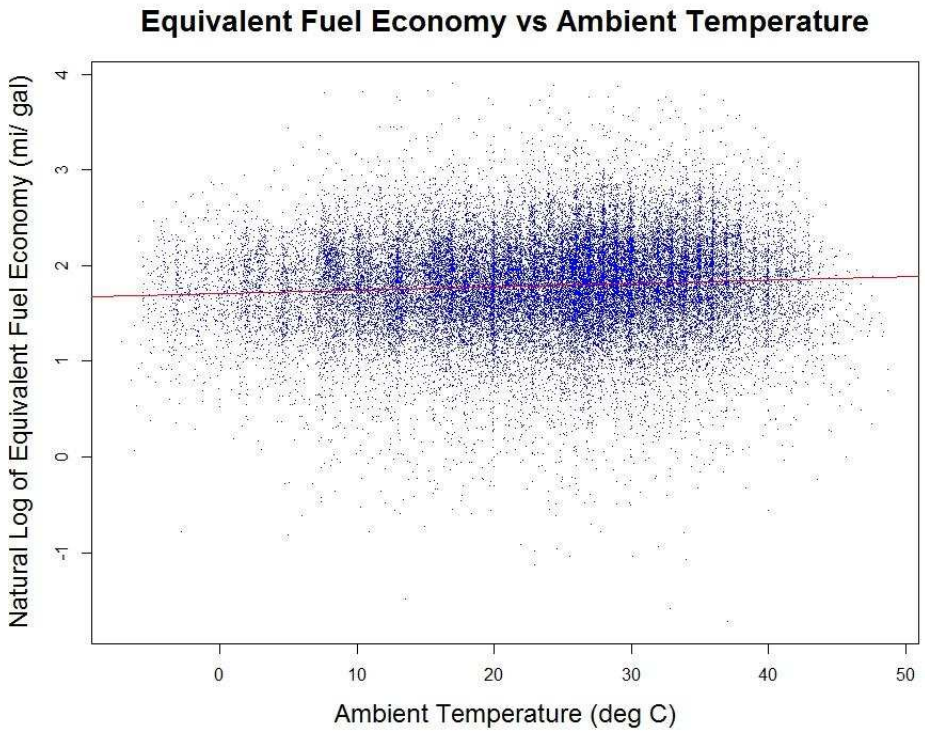

Figure 5.12 – Semi-Log Regression of Equivalent the Fuel Economy vs. Ambient Temperature

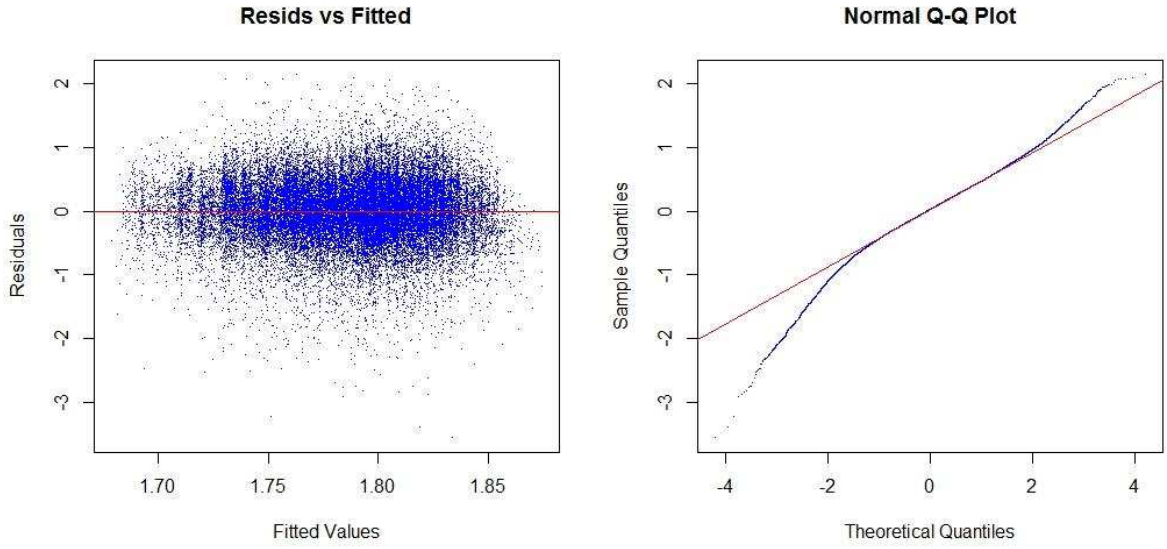

Figure 5.13 – Residual and Normal QQ-Plot for the Semi-Log Regression Model of Ambient Temperature vs. Equivalent Fuel Economy

```
> summary(Fit3)

Call:
lm(formula = log(1/equivalentFuelEconGalPerMile) ~ avgAmbientTempInC, data = filteredData)

Residuals:
 Min      1Q       Median  3Q      Max
-3.5584  -0.2876  0.0177  0.3175  2.1402

Coefficients:
                   Estimate   Std. Error  t value  Pr(>|t|)
(Intercept)        1.7035909  0.0064891   262.53   <2e-16 ***
avgAmbientTempInC  0.0035091  0.0002549   13.77    <2e-16 ***
---
Signif.  codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 0.5015 on 38751 degrees of freedom
Multiple R-squared: 0.004866,       Adjusted R-squared: 0.00484
F-statistic: 189.5 on 1 and 38751 DF, p-value: < 2.2e-16
```

Figure 5.14 - R Code Console Output for the Semi-Log Regression Model

Table 5.6 - Coefficients and Values for the Semi-Log Regression Model of Vehicle Efficiency vs. Ambient Temperature

Parameter	**Estimated value**	**p-value**
y-intercept (a)	1.7035909 (ln(mi/gal))	Less than $2x10^{-16}$
Slope (b)	0.0035091 (ln(mi/gal)/C)	Less than $2x10^{-16}$
R-squared	0.004866	N/A

Model is: ln(y) = a + bx = ln(equivalent fuel economy)

The trends seen in these graphs for vehicle efficiency follow the same pattern as the trends for conventional gasoline vehicles established in the 1980's [64]. In this EPA sponsored report titled *Temperature Correction Formulas for Adjusting Estimates of Automobile Fuel Consumption* [64] it can be seen on page 8 that fuel consumption is higher at lower temperatures, which corresponds to the lower fuel economy in miles per gallon seen in the Odyne fuel economy regression lines that were calculated by CSU. This makes sense, as the Odyne truck is still mostly a gasoline powered vehicle with mild-electric hybridization [15].

Therefore, the general qualitative ambient temperature trends from conventional gasoline vehicles can still be applied to mild hybrid PHEV vehicles such as Odyne Medium Duty Work Trucks. The similarities between the CSU model and this EPA model are further explored later in Subsection 5.6.1.

5.5.3 Vehicle Efficiency vs. Kinetic Intensity for Odyne

In addition to the ambient temperature results, vehicle efficiency was also regressed against other variables to look for other correlations. The most significant trend was found in the kinetic intensity [46]. Kinetic intensity (KI) can be used as a measure of driver aggressiveness with higher kinetic intensity values corresponding to more aggressive driving behavior. As would be expected, vehicle efficiency decreases as driver aggressiveness increases. The R plot below (Figure 5.15) shows this trend.

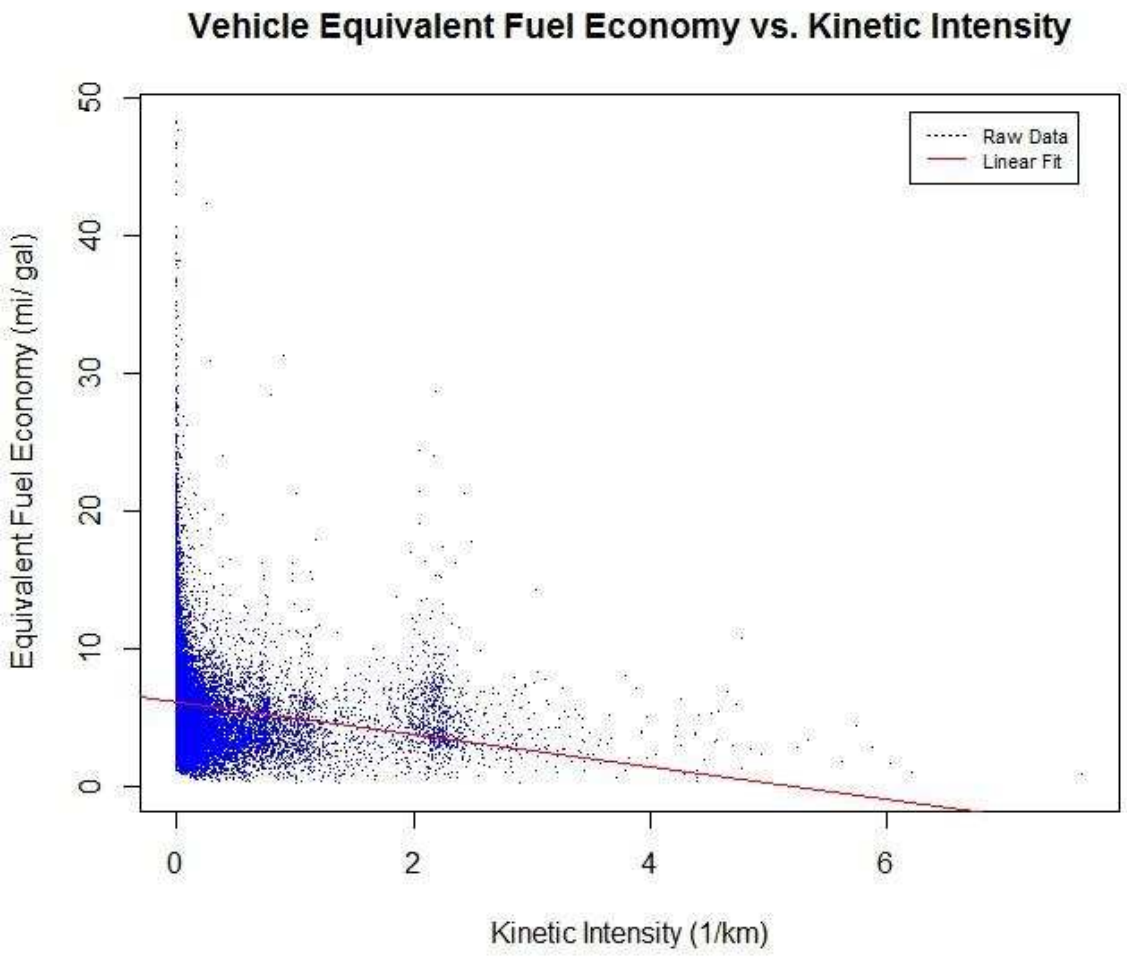

Figure 5.15 - Vehicle Equivalent Efficiency vs. Kinetic Intensity

The regression model for ambient temperature vs. kinetic intensity has the following parameters and R-console output (Figure 5.16 and Table 5.7):

```
> summary(Fit4)

Call:
lm(formula = 1/equivalentFuelEconGalPerMile ~ kinematicIntensityOneOverKm,
 data = filteredData)

Residuals:
 Min     1Q      Median  3Q     Max
-5.568  -2.003  -0.590  1.258  42.127

Coefficients:
                             Estimate  Std. Error  t value  Pr(>|t|)
(Intercept)                  6.1539    0.0171      359.85   <2e-16 ***
kinematicIntensityOneOverKm  -1.1784   0.0375     -31.42    <2e-16 ***
---
Signif.  codes:
0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 3.157 on 38759 degrees of freedom
Multiple R-squared: 0.02484,        Adjusted R-squared: 0.02482
F-statistic: 987.3 on 1 and 38759 DF, p-value: < 2.2e-16
```

Figure 5.16 - R Code Console Output for the Linear-Regression Model of Fuel Economy vs. Kinetic Intensity

Table 5.7 - Coefficients and Values for the Linear-Regression Model of Kinetic Intensity vs. Ambient Temperature

Parameter	**Estimated value**	**p-value**
y-intercept	6.1539 (mi/gal)	Less than 2.2×10^{-16}
slope	-1.1784 (mi*km/gal)	Less than 2.2×10^{-16}
R-squared	0.02482	N/A

The residual and QQ-plot for the equivalent fuel economy vs. kinetic intensity model are shown below in Figure 5.17. Like the previous linear model for ambient temperature vs. equivalent fuel economy, although the linear model is not the best model for the data, it does highlight that the basic trend is that fuel efficiency decreases as kinetic intensity increases. This is the expected qualitative result.

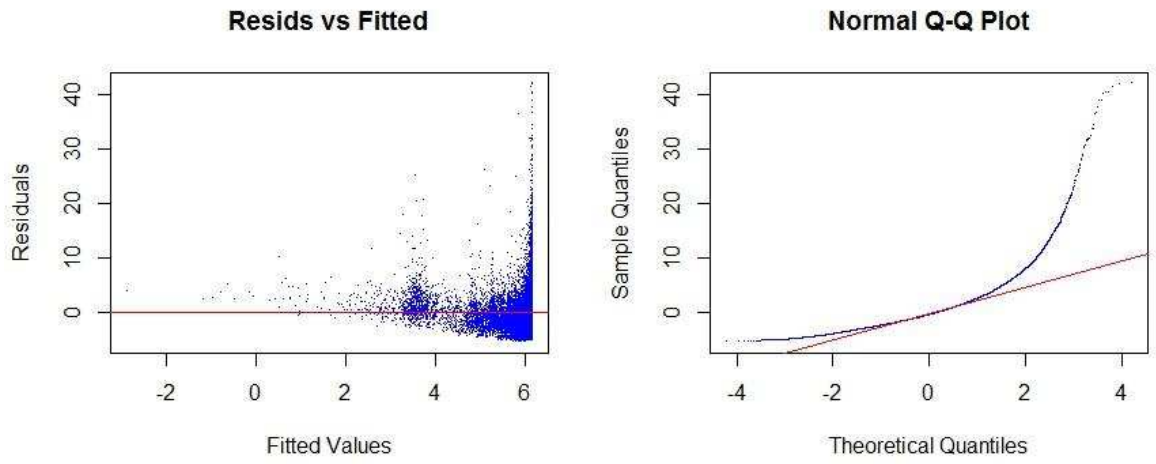

Figure 5.17 - Residual and QQ-Plot for the Linear Model of Equivalent Fuel Economy vs. Kinetic Intensity

5.5.4 Correlations between Vehicle Fuel Economy and Vehicle Drivetrain Calibration for Odyne

Another factor that was investigated to understand its correlation to the Odyne vehicle efficiency is the powertrain calibration. When an Odyne truck is programmed with a mild calibration, the vehicle uses more gasoline during its charge-depleting mode to save battery power. When the truck is programmed with an aggressive calibration, the vehicle uses less gasoline and more battery power during its charge-depleting mode. Since all of the collected data falls into these two discrete categories, a 2-sample-t-test is used to calculate the mean value for each category and the p-value. Before the statistical test was run, it was expected that the results would be statistically significant due to the very large sample size. The t-test is just an extra measure to ensure the significance of the results.

The two sample t-test shows that the fuel economy for the mild and the aggressive calibrations are very similar. The Welch-Satterthwaite method is used. The fuel economy during the charge-depleting mode for a vehicle programmed with a mild calibration is 6.705 mpg. The fuel economy during the charge-depleting mode for a vehicle programmed with an aggressive calibration is 6.791 mpg. These results are statistically significant as the p-value is 0.02345. However, since the calculated values are so similar, it is likely that this difference is not the most significant factor that influences vehicle fuel economy in the real world and is of debatable practical importance.

It should also be noted that filtering outliers has a large impact on all of the above results. For example, if the unfiltered data is instead used for the vehicle calibration 2-sample t-test, the mild calibration gets a fuel economy of 9.947 mpg and the aggressive calibration gets a fuel economy of 6.745 mpg. However, the p-value of $p = 0.2921$ for these results is not generally considered to be statistically significant.

A different result with a much larger p-value is also true for some of the other regression models presented in earlier subsections before the filtering was implemented, although the exact values for each regression model without this filtering are not presented in this thesis. However, as removing outliers is generally considered to be an acceptable statistical practice and the removed data points did not have realistic values, we believe that these results still meet acceptable statistical practices [65]. This filtering process was explained previously in more detail.

5.5.5 Correlations between Vehicle Efficiency and Other Variables for Odyne

In addition, some of the other signals are investigated for trends against the equivalent fuel economy in the old Odyne dataset. These include the HVAC signals and the cabin temperature signal.

Cabin temperature showed a similar correlation to vehicle efficiency as ambient temperature, which makes sense as the temperature inside the vehicle is often similar to the temperature outside the vehicle. The data from these results will not be directly presented in this thesis, but it is worth mentioning that they were investigated as well.

It was discovered that the heater and AC signals are not turned on enough to calculate any meaningful trend. It is theorized that AC and heater use might have an impact on vehicle efficiency in cold and warm temperatures and there are other studies that support that AC use impacts vehicle efficiency [42, 43].

5.5.6 Vehicle Efficiency vs. Ambient Temperature for Via

Of particular interest is the correlation between the electric fuel economy (in miles/kWh) of Via's pure-electric charge depleting mode and ambient temperature. Some initial evidence from work published by *Tugce Yuksel and Jeremy J. Michalek* suggests that the driving efficiency of pure electric vehicles has a different correlation to ambient temperature than gasoline vehicles [56].

To investigate this correlation in our own dataset, we used the same algorithm for Odyne with some minor code modifications to make it run on the new Via dataset. Unlike most of the other analysis presented in this paper, the new Via dataset that was hosted on AWS was used since that was the only way to access the ambient temperature signal. Unfortunately,

the final results from this analysis did not make sense. After the 90-second drive segments with a battery SOC of less than 22% were removed, the majority of the 90-second drive segments still had significant gasoline fuel usage reported by the algorithm. This contradicts what we understand about the Via powertrain from EPRI's report [15] and the Via Corporate Website [21, 22] which both state that Via operates with a pure-EV charge depleting mode.

Below in Figure 5.18 is a histogram that shows the distribution of the gasoline-only fuel economy in Via's charge-depleting mode without the equivalent electric fuel use included into the fuel economy calculation. It can be seen that a large number of the 90-second drive segments show significant fuel consumption. If data points where the reported fuel economy is greater than 0.001 gal/mile are removed from this dataset, the number of data points decreases from 121984 to 23205 which is about an 80% reduction. CSU concluded that this filtration step is removing too many data points for there to be confidence in final results so final results will not be presented here.

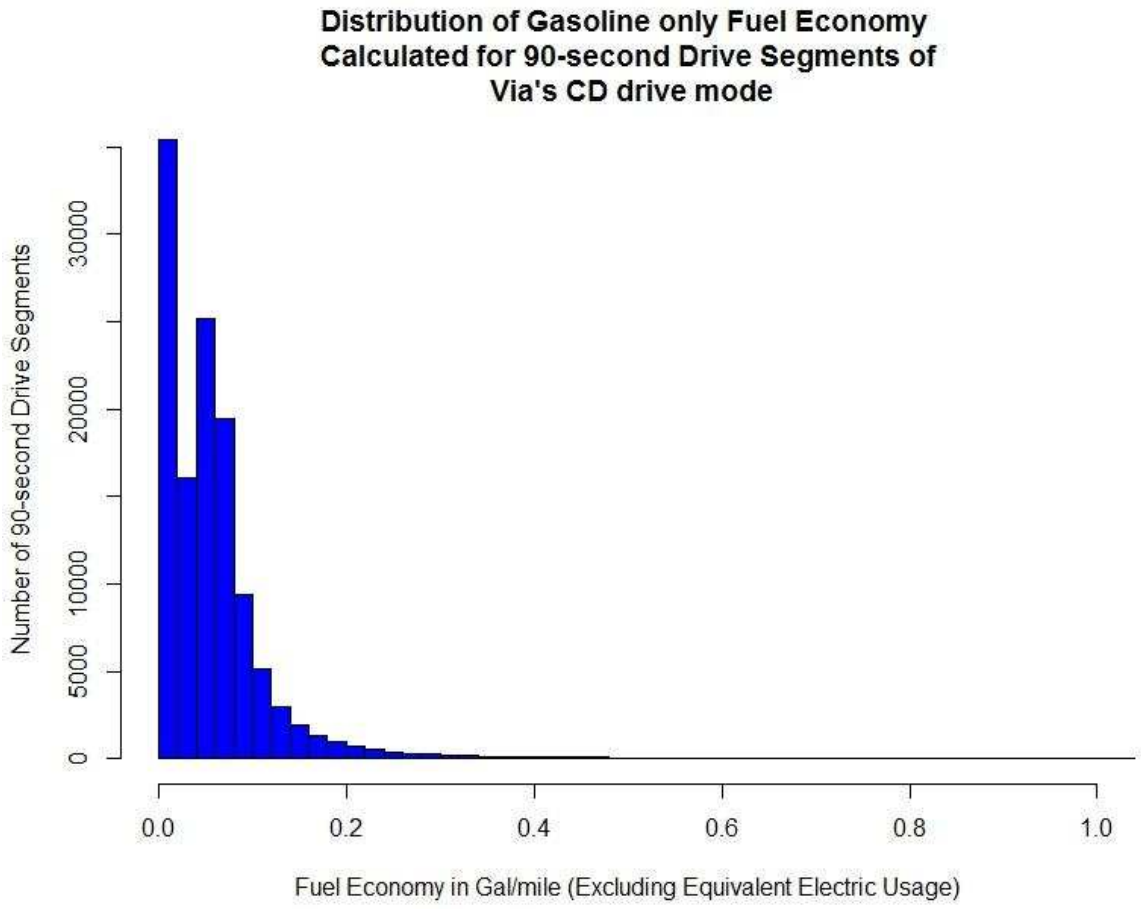

Figure 5.18 – Problem With the Via Recorded Gasoline Consumption in Charge Depleting Mode

It is unclear why so much fuel consumption is being reported for the Via platform when it is supposed to be in a pure-EV charge depleting mode. It is possible that the algorithm does not work when it is applied to other vehicle platforms or it is possible that our team could have introduced a bug into the software when it was converted to run on the Via dataset. It is also possible that there is a problem with the Via onboard data collection system or that we do not fully understand how the Via hybrid powertrain is operating in the real world. Or, it is also possible that some of the new Odyne data got mixed into the new Via data in the new database storage system that was only used for the Via analysis presented here. Finally, the general

impression of the Odyne vs. the Via dataset was that Odyne contained more accurate and complete data than Via so that could be part of the problem as well. All of these possibilities might be contributing to the problem.

Since there is uncertainty in these results, the correlation between equivalent fuel economy and ambient temperature for Via will not be presented. Hopefully future research can resolve these issues as the results of a pure-EV electric efficiency vs. ambient temperature are expected to be significant for the research community.

5.6 Discussion

5.6.1 Comparison of Odyne Fuel Economy vs. Ambient Temperature Trends to a Conventional Vehicle

We can use the Odyne results to understand the effect that ambient temperature has on the fuel economy of these vehicles. In this discussion section, we compare the fuel economy sensitivity to ambient temperature correlation that is calculated in this study for Odyne to the correlation calculated in another study.

First of all, in the 1980's the EPA commissioned a study to understand the effects of ambient temperature on conventional vehicle fuel economy [64] and the Odyne results presented here follow the same trend. The EPA study shows that at cold temperatures, vehicles in general use more fuel. At 0 degrees F in the EPA study, the gasoline engine uses approximately 1.14 times more fuel than it does when it is operating in the standard FTP temperature range of 68 deg F to 86 deg F [64][2]. This difference disappears once the ambient temperature reaches the lower bound of the FTP temperature range in the EPA study as the

[2] Data from the EPA study was derived graphically by using logarithmic interpolation on the graph presented on page 8 of this study. Results from the graphical interpolation are approximate.

number is a ratio to the FTP fuel consumption. This can be compared to our ambient temperature results from the EPRI Odyne dataset by dividing the predicted miles per gallon value from a point within the FTP temperature range (in this case (68 + 86) / 2 = 77 deg F) by the predicted miles per gallon at 0 degrees F. At 0 degrees F our semi-log model from the EPRI data predicts a fuel economy of 5.161 mpg. At 77 degrees F our semi-log model predicts a fuel economy of 5.997 mpg. This calculation results in a cold temperature increase in fuel consumption of 1.16 times when the cold-temperature fuel consumption is compared to the fuel consumption in the middle of the FTP temperature range. Again, these results are based on our real-world data model. As you can see, the fuel consumption increase of 1.16 times for Odyne is reasonably similar to the fuel consumption increase of 1.14 calculated in the EPA report for the same temperature [64].

Table 5.8 below shows a comparison of this ratio between our Odyne dataset and the EPA data over a range of other temperatures:

Table 5.8 - Comparison of the Fuel Economy vs. Ambient Temperature Results

Temperature (deg F)	**0**	**20**	**40**	**60**	**80**	**100**
EPA FE Ratio – For Conventional Gasoline Engines [64]	1.14	1.11	1.06	1.02	0.99	1.00
FE Ratio from our EPRI data (semi-log model) – for mild-hybrid electric Odyne trucks	1.16	1.12	1.07	1.03	0.99	0.96

It can be seen in Table 5.8 above that our Odyne dataset closely follows the EPA dataset. The biggest divergence occurs at 100 deg F because the EPA study uses a different semi-log model for temperatures about the FTP range whereas our study used a single semi-log model for the entire data range.

Since the Odyne truck is a mild hybrid and still produces most of its torque and power using a conventional diesel engine, it makes sense that the Odyne truck would follow the same general trend as a conventional vehicle. The electric motor on the Odyne truck only provides a small power assist to improve the fuel economy.

5.6.2 How Ambient Temperature Could Impact Fuel Economy at Temperature Extremes

According to EPRI the Odyne Trucks have a fuel economy rating of 6.07 mpg on the CILCC drive cycle when they are programed with a mild-calibration setting that depletes the battery more slowly [15]. Assuming that this drive cycle test was performed at room temperature (23 deg C), our semi-log model from the EPRI Odyne data suggests that temperature could influence the fuel economy results by increasing the equivalent fuel economy by 6% when the temperature is increased to 40 deg C or lowering the equivalent fuel economy by 11% when the temperature is reduced to -10 deg C. These differences could have meaningful real-world impacts. These percentages are calculated from our semi-log model where the fuel economy at 23 deg C is 5.955 mpg, the fuel economy at 40 deg C is 6.321 mpg, and the fuel economy at -10 deg C is 5.304 mpg. Percentage results for Odyne are calculated by dividing the extreme temperature fuel economy by the standard fuel economy at 23 deg C. .

5.6.3 The Potential Impact of HVAC on Fuel Economy

In addition, as discussed earlier in Subsection 5.5.5, the AC and heater were almost never turned on according to the data analysis of the old Odyne dataset so our real-world data is expected to be closer to the type of data in the EPA report that is based on drive cycle testing. HVAC is generally not accounted for during an EPA drive cycle test. However, it is known that AC can impact the fuel economy of a vehicle so if the heater and AC were used in the Odyne Trucks these results could have been much different. In work published by *Kiran Kambly and Thomas H. Bradley* [42, 43], the effects of ambient temperature and HVAC use on vehicle efficiency were investigated. In Detroit Michigan, it was shown that the all-EV range of PHEVs varied between 65 and 79 miles and this variation was due to differences in ambient temperature conditions and HVAC use [43]. Therefore, if the HVAC systems of the Odyne trucks were more widely used, this could impact the equivalent fuel economy vs. ambient temperature curve by lowering the fuel economy at extreme cold and hot ambient temperature conditions. Another dataset with more HVAC usage would be needed to quantitatively determine the impact of HVAC on Odyne fuel economy and verify that it changes the fuel economy in this situation. Or, it is also possible that there is a glitch in our data analysis software and that is why we are seeing these results.

SECTION 6

DISCUSSION

6.1 Why the Methodologies behind Big Transportation Fleet Data Analysis Need to be Better Defined

Many studies have presented the final results of fleet data analysis [1, 15, 43, 48, 49, 50, 51, 52, 53, 54, 55, 56, and 57] but few of these studies really provide a detailed description of the analysis methodologies, assumptions, and intermediate data processing steps that were used to draw their conclusions. Having done this type of fleet data analysis work myself at Colorado State University, my experience has been that the final results can be dependent on the assumptions, filtering techniques, data manipulations, and other intermediate steps that are used to produce the results. More work is needed to understand the impact of these data processing steps, how they affect the final results, and what data processing steps represent the "best practice" for analyzing vehicle fleet-tracking big data.

6.1.1 The Impact of Outlier Filtering Just before the Regression Model is Calculated

For example, as previously discussed in Subsections 5.4 and 5.5.4, if outliers are not filtered out in the intermediate data after the Phase 2 processing and just before the regression model is drawn, different results that are not statistically significant are generated. If the unfiltered data is instead used for the vehicle calibration 2-sample t-test, the mild calibration gets a fuel economy of 9.947 mpg and the aggressive calibration gets a fuel economy of 6.745 mpg with a p-value of $p = 0.2921$. This is very different than the mild-calibration fuel economy of 6.705 mpg, the aggressive-calibration fuel economy of 6.791 mpg, and the p-value

of p = 0.02345 that were calculated when outlier data filtering was applied. Table 6.1 below summarizes these differences:

Table 6.1 - Comparison of Fuel Economy and P-Values With and Without Outlier Filtering

	With Outlier Filtering	**Without Outlier Filtering**
Mild-Calibration Fuel Economy (mpg)	6.705	9.947
Aggressive-Calibration Fuel Economy (mpg)	6.791	6.745
p-value	0.02345	0.2921

6.1.2 The Impact of Continuously Evaluating the Drive Condition in the Data Analysis Software

The above example about removing outliers is a common statistical practice that is fairly well known. However, to process vehicle fleet-tracking data our team also had to develop a number of more obscure methods that are very specific to this type of data analysis. For example, another known problem with the raw data is the data collection system only collects data when the vehicle is operating. Therefore, data collection may begin a few seconds after the vehicle turns on and recorded values such as the vehicle speed and battery current do not start at zero like you would expect in perfect theoretical data. The graph below in Figure 6.1 shows an example from the raw Odyne data where the battery current signal does not start at zero. You can see how MATLAB interpolates the battery current in a straight line over a time span of about two days, because the first battery current data point collected was approximately -40 Amps when the vehicle turned on again. However, since the vehicle only

uses battery power when the vehicle is on, the true battery current that occurs immediately when the vehicle turns on should be very close to zero.

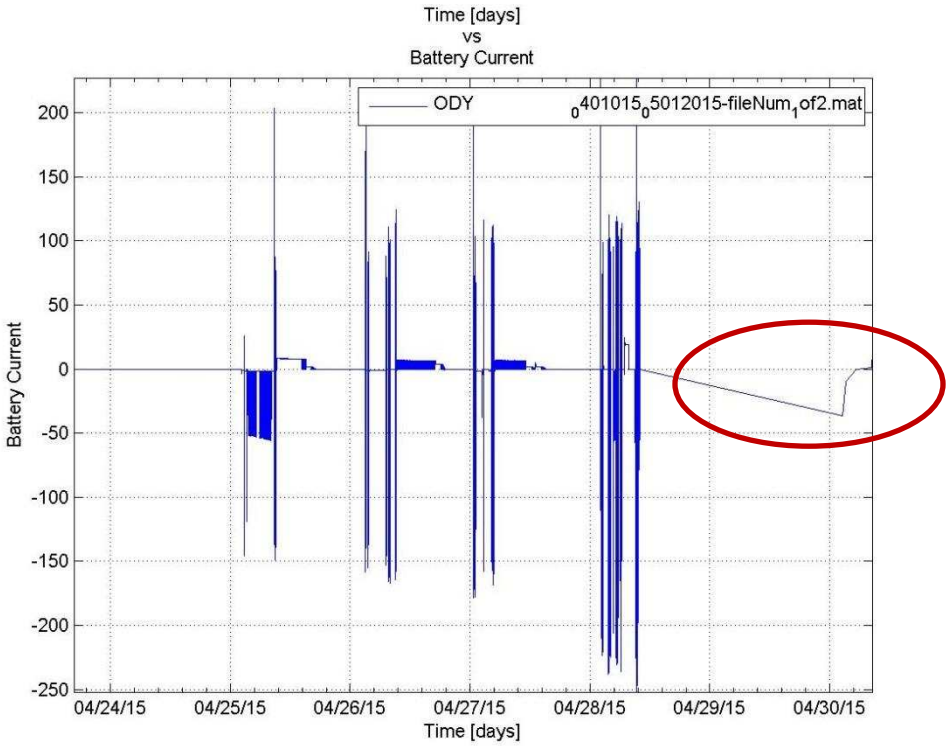

Figure 6.1 - Raw Battery Current Signal (Amps) Does Not Start at Zero as Seen in the Interpolation Error

This is a very specific problem with vehicle tracking data. The next question is, what problems can this cause and how do we deal with it? In our process described in Section 4, the analysis code does not look for trigger events when a threshold is crossed, such as when the vehicle speed transitions from a near zero to positive value, to identify when the vehicle starts and stops driving. Instead, the analysis code defines a continuous condition that is applied to all of the data points to check if the vehicle speed is greater than zero. This way, if the data collection system misses the initial few seconds when vehicle speed transitions from 0 mph to positive, the driving event identification algorithm can still figure out that the vehicle is driving

even if the first driving speed data point is at, let's say, 30 mph. This is a very subtle difference in the analysis methodology, but it can have real impacts on the results.

For example, the data in Figure 6.2 below shows drive event summary data that was compiled by a different, preliminary algorithm while it was still under development at another EPRI contractor (independent of CSU). This algorithm had problems properly identifying where charging events should occur as can be seen in the below results. In Figure 6.2 below that shows the event summary data, there should be a charging event between the highlighted driving events, especially when the second drive event begins with the battery mysteriously recharged. After conversations with EPRI's software contractor, CSU realized that one of the reasons behind these problems was that their algorithm only checked if the signal was transitioning across a threshold and did not consider if the initial value was already beyond the threshold.

	Event	Mode	Date At Beginning (mm/dd/yyyy)	Time at Beginning (hh:mm:ss GMT)	Duration (min)	Ending Odometer (mi)	Kinetic Intensity (1/ft)	SOC Beginning (%)	SOC Delta (%)	Ex Us
113	TRACTION	Charge Sustaining	1/14/2015	19:56:09	18.5	2857	0	16	-15	<N
114	TRACTION	Charge Sustaining	1/14/2015	20:21:29	1.2	2857	<Not Applicable>	1	-0.5	<N
115	TRACTION	Charge Sustaining	1/14/2015	20:23:12	1.1	2857	<Not Applicable>	0	0	<N
116	TRACTION	Charge Depleting	1/15/2015	15:48:51	18.3	2866	0	83	-23.5	<N
117	STATIONARY	Hydraulic	1/15/2015	16:09:15	9.5	2866	<Not Applicable>	58.5	-6	
118	STATIONARY	Hydraulic	1/15/2015	16:19:10	175.1	2866	<Not Applicable>	52.5	-45.5	
119	TRACTION	Charge Sustaining	1/15/2015	19:18:24	22.9	2873	0	8.5	-7.5	<N
120	STATIONARY	Hydraulic	1/15/2015	19:43:05	1.3	2873	<Not Applicable>	3.5	0	
121	TRACTION	Charge Depleting	1/15/2015	19:50:55	1.8	2873	<Not Applicable>	4	-0.5	<N
122	TRACTION	Charge Sustaining	1/15/2015	20:01:41	1	2873	<Not Applicable>	3.5	-1	<N
123	TRACTION	Charge Sustaining	1/16/2015	5:18:15	1.2	2873	<Not Applicable>	3.5	-1	<N
124	STATIONARY	Hydraulic	1/16/2015	5:19:45	1.3	2873	<Not Applicable>	2.5	0	
125	STATIONARY	Hydraulic	1/16/2015	5:21:09	24	2873	<Not Applicable>	2.5	21.5	
126	TRACTION	Charge Sustaining	1/16/2015	5:54:02	26.6	2884	0	27	-25.5	<N
127	TRACTION	Charge Sustaining	1/16/2015	7:26:08	1.1	2884	<Not Applicable>	1	-0.5	<N
128	TRACTION	Charge Sustaining	1/16/2015	7:33:33	1.1	2881	<Not Applicable>	1	-0.5	<N
129	TRACTION	Charge Sustaining	1/16/2015	10:40:52	19.7	Unknown	<Not Applicable>	0.5	0.5	<N
130	TRACTION	Charge Sustaining	1/16/2015	11:02:48	1.4	Unknown	<Not Applicable>	1.5	-0.5	<N
131	TRACTION	Charge Sustaining	1/16/2015	11:05:52	1.4	Unknown	<Not Applicable>	1	0	<N
132	TRACTION	Charge Sustaining	1/16/2015	11:17:22	1.6	Unknown	<Not Applicable>	1	-0.5	<N
133	TRACTION	Charge Depleting	1/19/2015	14:13:13	10.8	Unknown	<Not Applicable>	100	-14	<N
134	TRACTION	Charge Depleting	1/19/2015	14:24:10	6.7	Unknown	<Not Applicable>	86	-6.5	<N
135	STATIONARY	Hydraulic	1/19/2015	16:07:48	41.9	Unknown	<Not Applicable>	83	-21	
136	STATIONARY	None	1/19/2015	16:50:14	45.2	Unknown	<Not Applicable>	62	2.5	
137	STATIONARY	None	1/19/2015	17:35:27	134.9	Unknown	<Not Applicable>	64.5	1.5	
138	TRACTION	Charge Depleting	1/19/2015	19:50:27	15.7	Unknown	<Not Applicable>	66	-19	<N
139	CHARGE	Level 2	1/19/2015	20:13:44	61.7	Unknown	<Not Applicable>	47	11.5	<N
140	TRACTION	Charge Depleting	1/19/2015	21:15:52	1.1	Unknown	<Not Applicable>	58.5	0	<N
141	TRACTION	Charge Depleting	1/19/2015	21:42:47	1.1	Unknown	<Not Applicable>	57	0	<N

Figure 6.2 - Event Summary List That is Missing Charging Events Between Driving Events.

On the other hand, the CSU algorithm had a continuous logic condition that would evaluate every data point to see if it was above the threshold so it would not get confused if the raw data was missing the initial transition from a zero to positive value. We found that our own algorithm produced much better results. These little details in the data analysis methodology can make a significant difference.

6.1.3 The Impact of Fuel Economy Averaging Techniques and Other Differences between CSU and EPRI Fuel Economy Results

Finally, one additional example will be presented. EPRI independently analyzed the same dataset and they came up with slightly different fuel economy results for the Odyne trucks than were calculated here at CSU. In addition, EPRI calculated two different fuel economy values in their report that were based on different analysis methodologies [15]. In

EPRI's report on their Figure 3-28 [15] (NOT Figure 3-28 in this thesis), they list the mild-calibration fuel economy as 5.8 (± 1.5) mpg and the aggressive-calibration fuel economy as 6.1 (± 1.6) mpg for Odyne. However in the EPRI report on their Figure 3-41, they list the mild-calibration fuel economy as 6.19 mpg and the aggressive-calibration fuel economy as 6.65 mpg. In addition, for comparison, CSU calculated the mild-calibration equivalent fuel economy to be 6.71 mpg and the aggressive-calibration equivalent fuel economy to be 6.79 mpg based on the data analysis process described in Section 5 of this thesis.

If everyone is using the same data to calculate these results, why are all of these numbers different? One difference between the EPRI and CSU analysis is that CSU is reporting an equivalent fuel economy that factors the electricity usage into the fuel economy whereas EPRI is reporting the diesel only fuel economy. However, if the EPRI fuel and electric fuel economies from their Figure 3-28 [15] are combined into an equivalent fuel economy, we still see a difference between the EPRI and CSU fuel economy values.

By using data from EPRI's Figure 3-28 in their report [15], the mild-calibration equivalent fuel economy was calculated to be 5.58 mpg and the aggressive-calibration equivalent fuel economy was calculated to be 5.53 mpg. This calculation was performed by combining the diesel only fuel economy with the average drive energy / distance data that is provided in the same table. The same formula that was used for the CSU equivalent fuel economy calculation in the Phase 2 MATLAB process described in Subsection 5.3 was applied to the EPRI data. Note that fuel economy decreases when electric energy is accounted for, as more energy use is being reported. Our equivalent fuel economy calculations could have possibly been improved by accounting for fuel vs. electric efficiency ratios as well, but this was not implemented into our software.

Table 6.2 below compares these different fuel economy numbers for all of the different situations described above. It should be noted that all of the different reported fuel economy values fall within EPRI's reported tolerance range for the data reported in Figure 3-28 in their report [15] so this is a positive indication that the different results provide a reasonable approximation of the true fleet fuel economy.

Table 6.2 - Comparison of Different Odyne Fuel Economies Calculated Using the Odyne Real-world Data

	CSU Analysis Results	**EPRI Analysis Results from their Figure 3-41 (diesel only fuel economy) [15]**	**EPRI Analysis results from their Figure 3-28 (diesel only fuel economy) [15]**	**Calculated equivalent fuel economy from EPRI results in their Figure 3-28 [15]**
Mild-Calibration Fuel Economy (mpg)	6.71	6.19	5.8 ± 1.5	5.58
Aggressive-Calibration Fuel Economy (mpg)	6.79	6.65	6.1 ± 1.6	5.53

Another difference between the different methodologies developed by EPRI and CSU is how the data is being averaged. In EPRI's Figure 3-28 in their report [15], the average fuel economy is calculated by dividing the total number of miles driven by the fleet by the total amount of gasoline used by the fleet. However, in EPRI's Figure 3-41 in their report [15], they are averaging the daily average fuel economies presented as a distribution in their histogram. Although neither of these two methods is necessarily "right" or "wrong", they are also not mathematically equivalent and should be considered different statistical measures. For another comparison, the CSU fuel economy calculation used neither of the two EPRI methods

described above. At CSU, we averaged the average fuel economies over 90-second drive intervals, which is different than averaging the average-daily fuel economies. This raises some questions. How should average fuel economies be reported for this type of work and do these differences matter? It will be left to future researchers to answer this question.

There are other differences between the EPRI and CSU data analysis processes as well since they were developed independently. For example, EPRI calculated drive events by using the key on/off signal to identify where a drive event was occurring whereas CSU checked if the vehicle speed signal was greater than zero. Or, CSU only used data from charge depleting (CD) drive events whereas EPRI used all drive data. In addition, EPRI may have a wider range of data as CSU only used a subset of the total dataset. There could be other unknown methodology differences between the EPRI and CSU results as well.

Overall, all of these methodology differences could be contributing to the difference in the final results. Depending on the accuracy needed, it will be left up to the reader and future researchers to determine if the differences between these fuel economy numbers is practically significant enough to pose a risk to their application or reported fuel economy results. The good thing is that all of the presented numbers are reasonably close to each other so they could each be used as a valid estimator of the unknown real-world fuel economy.

6.1.4 Conclusion: Why More Data Analysis Methods Need to be Better Defined

A few examples of why methodologies need to be defined for analyzing vehicle fleet-tracking data were presented with evidence. As can be seen in Sections 4 and 5, there are many other data processing steps that could influence the final results which are not discussed in this discussion section. A flaw in any of these steps could produce inaccurate scientific

results that would mislead policy makers, fleet owners, and vehicle designers. My research team believes that there needs to be a published "cookbook" of methodologies for analyzing vehicle fleet-tracking data and we hope that the work presented in this thesis can lay an initial foundation to begin a discussion about how these best practices should be defined. There is plenty of room for future researchers to build on the work in this thesis by evaluating the effectiveness and impact of each individual data processing step and by developing new data analysis techniques.

6.2 Advantages of Making Decisions Based on Real-World Fleet Data

This section outlines some of the potential benefits of using real-world fleet data to make operational and policy decisions. Real-world data can provide an alternate evaluation method to EPA drive cycles and it can also be used to calculate the real-world utility factor.

6.2.1 Real-World Data Provides an Alternate Evaluation Method to EPA Drive Cycles

Historically, the standard method to evaluate vehicle emissions and fuel economy was testing the vehicle on an EPA drive cycle [66]. These drive cycles define exactly what speed the vehicle should be driving at over time and are typically 700 to 1000 seconds long. The tests are normally performed on a dyno setup, which is a highly controlled environment. This provides great experimental repeatability for different vehicle platforms to be tested against. However, there are also disadvantages to using EPA drive cycles.

One disadvantage of EPA drive cycles is the assumption that a 10-minute test can accurately represent real-world driving behavior. Other studies have investigated this and many have found that drive cycles often produce different results than those produced using

real-world data [11, 52, 67, and 68]. In theory, results calculated from real-world data should accurately represent how the vehicles performed in the real world so real-world data has the potential to provide more accurate information about vehicle use, emissions, and fuel economy to policy makers. It is debatable if a 1000-second drive cycle can fully capture all of the intricacies of driving behavior and vehicle use such as the weather conditions experienced, differences in driving behavior between individual drivers, local traffic laws, variations in traffic conditions, and changes in vehicle performance due to aging. However, collecting real-world data accounts for all of the factors that can possibly affect vehicle performance whether those factors are known or unknown. Below is some sample data from our own work to demonstrate this.

For example, according to EPRI the Odyne Trucks have a fuel economy rating of 6.07 mpg [15] on the CILCC drive cycle [69] when they are programed with a mild-calibration setting that depletes the battery more slowly [15]. Odyne trucks programmed with an aggressive-calibration setting have a fuel economy rating of 7.72 mpg on the same drive cycle [15]. On drive cycle tests, the aggressive calibration gets better fuel economy than the mild calibration. However, in our final data calculation from the code described in Section 5, CSU found that the fuel economy was very similar for the mild and aggressive calibrations. The average equivalent fuel economy for a mild calibration was 6.71 mpg and the average equivalent fuel economy for an aggressive calibration was 6.79 mpg based on the data analysis work performed at CSU on the real-world Odyne truck dataset. This illustrates that the fuel economy can be different when it is calculated using an EPA drive cycle vs. using real-world data.

In addition, different EPA drive cycles produce different fuel economy results. On the OCTA drive cycle the Odyne trucks get an average fuel economy of 4.44 mpg for a mild calibration and an average fuel economy of 5.57 mpg for an aggressive calibration [15]. Or, on the HHDDT drive cycle [69] the Odyne Trucks get an average fuel economy of 5.46 mpg for a mild calibration and an average fuel economy of 7.09 mpg for an aggressive calibration [15]. The differences between the different EPA drive cycle results raises the question of which EPA drive cycle most accurately represents real-world driving. The fuel economy from all of these EPA drive cycle tests and our real-world results are summarized below in Figure 6.3. As can be seen, there are differences between our real-world fuel economy calculations and the fuel economy calculations from the different EPA drive cycles.

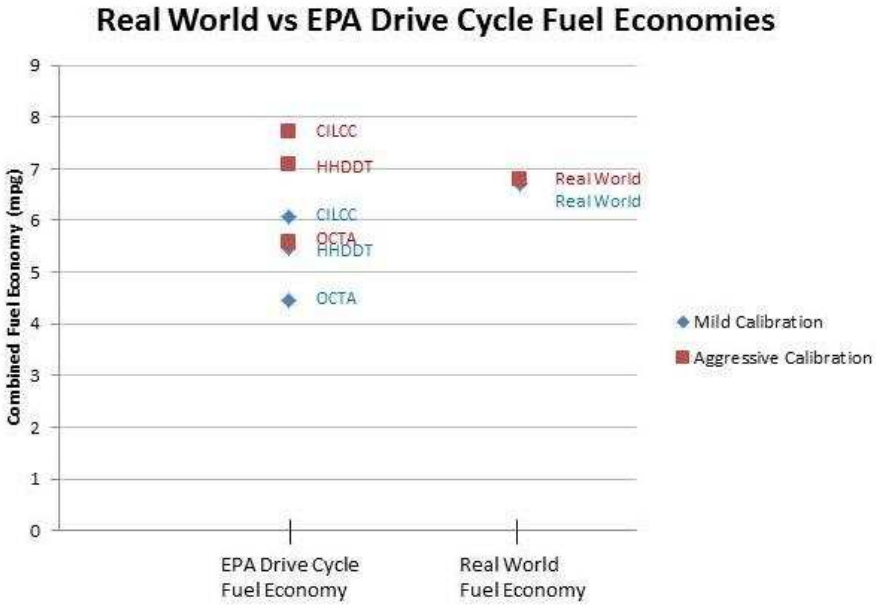

Figure 6.3 - Real World vs. EPA Drive Cycle Fuel Economy Comparison [15]

Finally, real-world data collection is important because EPA drive cycles are susceptible to cheating, such as in a recent incident involving Volkswagen that was heavily

publicized in the news [70, 71]. In this scandal, Volkswagen programmed their vehicles to run the engine differently to reduce emissions when its control system recognized an EPA drive cycle pattern. These discrepancies were first noticed when researchers started measuring the emissions of vehicles driving in the real world. Therefore, real-world data such as the EPRI data used in this study can be used to verify that OEM's are not programming their vehicles to cheat EPA drive cycle tests. When large-scale real-world data collection is implemented, OEM's who build vehicles have to make their vehicles emit appropriate emissions because it is very difficult to cheat the real world.

6.2.2 Real-World Data Can be Used to Calculate Real-World Utility Factors

A utility factor, such as the utility factor (UF) curves presented in Section 4.4.1 and presented in previous work [1, 41, 49, 55, and 60], is needed to calculate the environmental impact of a range-extending vehicle such as a PHEV. Utility factor is a proportion that tells what proportion of driving distance is being powered in a charge-depleting drive mode where electric energy from the utility grid is used. For example, a utility factor of 80% means that 80% of the driving distance occurs in a charge-depleting mode that is using power from the electric utility grid. If the PHEV has an all-EV charge depleting mode, the utility factor represents the actual proportion of the driving distance that was only powered by the electric utility grid.

Utility factor is frequently presented as a graph of UF vs. the charge-depleting range of the battery (RCD) so vehicle designers can make trade-off decisions about what battery size is needed in the vehicle. A large onboard battery will increase the UF as the vehicle will then be able to make longer trips on a single charge. However, there are also diminishing returns in

UF improvement as the battery size continues to increase as there are generally fewer and fewer people making longer and longer trips. Utility factor is also highly dependent on driving behavior, as drivers who mostly take very short trips and recharge in between will have a much higher UF than drivers who take their PHEV vehicles on long-distance trips across the country.

The SAE J2841 standard is commonly used to define UF [60], but different vehicle platforms and real-world effects can influence the UF to be different in specific situations [41]. Real-world driving data is needed to determine how a specific subset of vehicles might differ from the SAE J2841 standard UF curve. In addition, the SAE J2841 standard UF curve was based on NHTS data which is self-reported by drivers in the study [47] so vehicle sensor data such as the data used in our study may provide more accurate results and eliminate human error.

For example, the following figure (repeated from Subsection 4.4.1 and relabeled Figure 6.4) shows how the Odyne UF curve that was calculated from our dataset differs from the standard SAE J2841 UF curve.

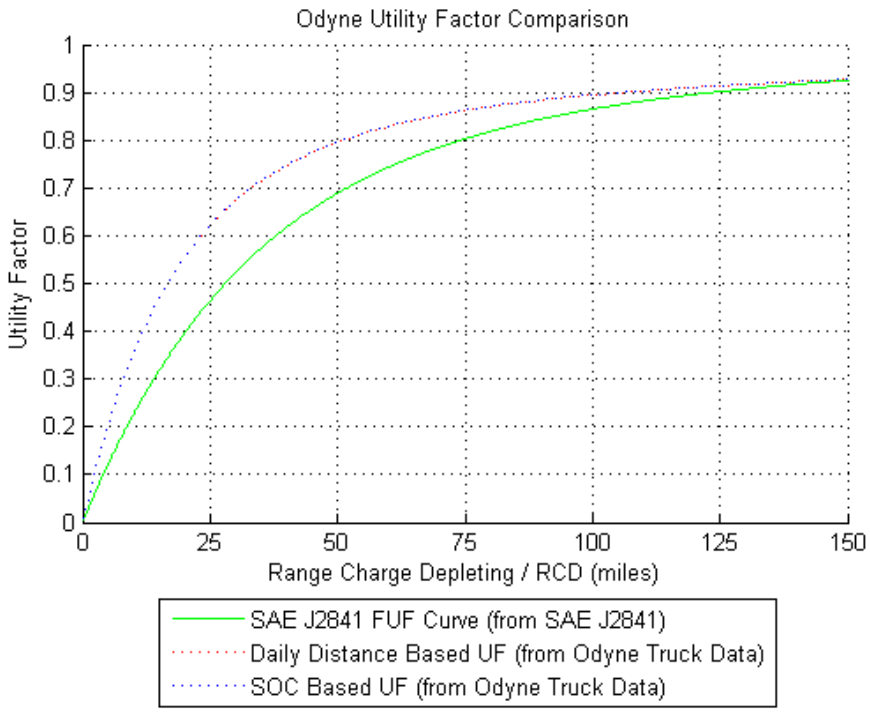

Figure 6.4 - Odyne Utility Factor Curves

In addition, the Via UF graph (repeated from Subsection 4.4.1 and relabeled as Figure 6.5) shows that there is a smaller difference from the standard UF curve than is seen in the Odyne UF graph. However, there is still a difference. For a Via battery with 25 miles of range, the standard SAE2841 curve indicates that the vehicle would power approximately 56% of its driving using power from the electricity grid. However, the UF curve calculated using real-world data indicates that the Via vehicle would power approximately 52% of its driving using power from the electricity grid using the same sized battery. This difference could still be large enough to make a real-world impact depending on the required accuracy.

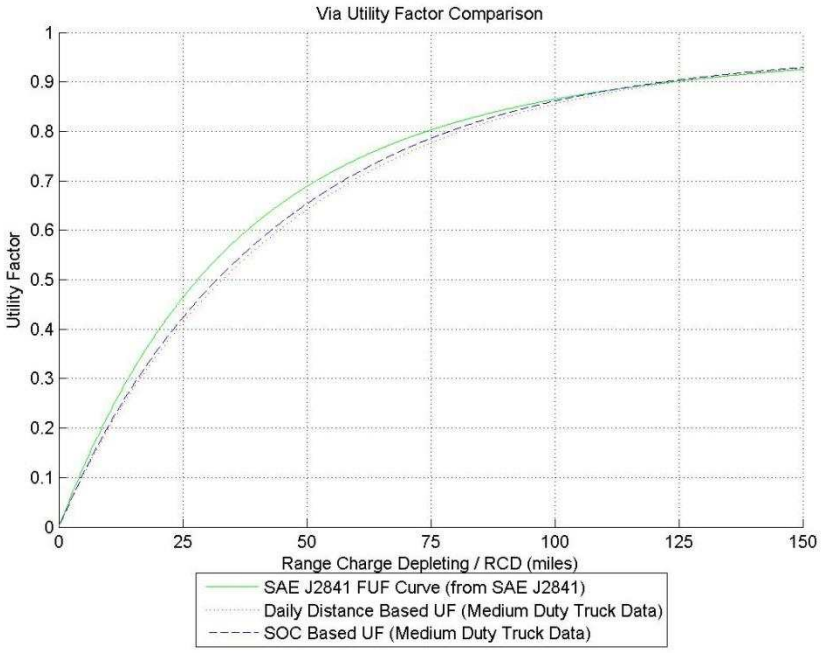

Figure 6.5 - Via Utility Factor Curves

6.3 How Valid Are These Final Data Analysis Results?

After considering the presented information and the discussion so far, considering if the results are valid is a fair question to ask. The short answer to this question is: maybe, but more work is needed to better define and understand the data processing methodologies for vehicle fleet tracking data.

6.3.1 Reasons Why Our Final Results Might Be Valid

In addition to the discussion presented previously in Subsection 6.2 about the benefits of using real-world fleet tracking datasets, one could argue that since our results for the ambient temperature vs. vehicle efficiency calculation are so similar to the previous EPA study for conventional vehicles, this is a positive indication that the results could be reasonably accurate. Odyne did not produce any outrageous results that were totally unrealistic so this is

also a good indication that supports the validity of our results. For example, our real-world average fuel economy (presented previously in Figure 6.3) falls within the range of the different EPA drive cycle tests so it may be a valid estimator of real-world fuel economy.

Since our fuel economy results are close to the EPA drive cycle results and the independent EPRI analysis on the same dataset, this provides additional evidence that our analysis method is providing a reasonable approximation for the average fuel economy. These results were discussed previously in Subsection 6.1.3.

Finally, because the Via is likely driven in a similar manner to other light-duty vehicles, it seems reasonable that its utility factor curve (presented earlier in Figure 6.5) is close to the J2841 standard utility factor curve. As documented in this thesis, a large number of data filtering, quality control steps, and intermediate data output were built into the data analysis process so this should help improve the accuracy of the results.

In addition, 2 years of software development work was invested into implementing this algorithm and my research advisor Dr. Bradley has a lot of experience doing this type of research in other studies [1, 8, 41, 42, 43, 49, and 55]. Therefore, I had some time to perfect and iterate the data analysis software, and the broader expertise of my lab group to draw on.

6.3.2 Reasons Why Our Final Results Might NOT Be Valid

On the other hand, as discussed previously in Subsection 6.1, there is really no standard process or methodology to analyze this kind of data. Many of the controlling values in the script, such as the 90-second target chunk size output by the Phase 1 MATLAB data processing module described in Subsection 5.2, were just determined holistically to provide a starting point. A strict analytical procedure was not used to derive most of the controlling

values in the filtration and data manipulation process. It is possible that a more rigorous scientific process could optimize and refine these parameters. In addition, the sensitivity of the results when the individual data filtering parameters are changed was not evaluated. This adds uncertainty to results.

Additional data validation could improve the confidence in the results. An independent software development effort to re-write the implementation of the algorithms described in this thesis would help verify that results are not being influenced by a software bug. In addition, independent measurements could be taken on the vehicles using a different data collection process to confirm that the data collection system and this algorithm are producing realistic results for a small number of vehicles.

In addition, the fundamental usage patterns of the Odyne and Via fleets could be biased and not representative of the entire population of vehicles, so unknown inaccuracies in the results could be a function of the raw dataset itself. Although the vehicles are scattered around the continental United States, they are also mostly owned by electric utility companies. It is possible that other commercial applications would result in different usage patterns for these vehicles. Currently, it is unknown what other biases may be present in the EPRI Commercial Truck dataset. The only conclusion that can be made with confidence is that the Odyne and Via datasets are representative of how Odyne and Via trucks were used during this study. An open question is how representative the EPRI Commercial Truck dataset really is for light- and medium-duty trucks in general. Additional analysis work using other datasets could help clarify how representative our results are of light- and medium-duty trucks.

The failure to apply the data analysis methodology for the ambient temperature vs. equivalent fuel economy calculation to the new Via dataset raises some questions as well (see

Subsection 5.5.6 for more details). Is the significant fuel usage in the Via results when it is supposed to be driving in an all EV-CD mode due to a problem with the data analysis methodology? Or is this due to a problem with the data collection system, or even an incomplete understanding of how the Via hybrid powertrain operates? More work is needed to answer this question.

Finally, there could be unknown errors and problems in EPRI's custom data collection system or the CAN-communication systems that were installed by Odyne and Via. At CSU, we were not responsible for installing the data collection system or decoding the CAN signals. All of that work was performed by EPRI and its contractors. Therefore, all of our work is based on the assumption that this data collection work was done to an acceptable standard of quality.

6.3.3 Conclusions About the Overall Level of Confidence in These Results

It will be left up to the reader and the expertise of future researchers to make their own conclusions about the validity of the results presented here. For example, although the data analysis methodology could be further developed and validated, maybe the final results generated by this study are still good enough to use until better data becomes available. On the other hand, if the open questions about our data collection and analysis methodology invalidate the presented results, this also potentially calls into question the results presented in many other research studies that rely on vehicle fleet-tracking big data [1, 15, 43, 48, 49, 50, 52, 53, 54, 55, 56, and 57]. Some of the studies cited here do not even mention what software / programming language was used to analyze their data [48, 54, 55, and 56]. In addition, it is possible to find

many other studies that rely on vehicle fleet-tracking data that are not cited here. Many of these studies need to do a better job of defining their data analysis methodologies.

It should also be mentioned that some of studies referenced here use different types of datasets other than CAN-communication bus data. These datasets include information such as GPS tracking data [50, 54, and 57] or driver reported data from a dataset such as the NHTS survey [43, 47, 49, 55, and 56] so different methodologies may be needed for these different types of datasets. Although the EPRI Commercial truck dataset contained both CAN and GPS data, only the CAN data was used for the results presented in this thesis. Finally, many of these studies are based on data collected from a larger number of vehicles than were available for the results presented in this study [48, 49, 50, and 54] so more data processing and analysis was potentially needed in these situations.

What all of the papers cited in the previous two paragraphs have in common is that they are all trying to derive conclusions from real-world vehicle data. Other studies do make an effort to define some of the methodologies and data collection systems that can be used to collect and process this type of data [51, 52, 54, 57, and 72]. Overall however, the lack of detail provided by the research community makes it hard to evaluate the rigor of the methodologies used by other researchers and compare them to our own methods. More details and documentation of the data analysis methodologies, assumptions, and data-filtration steps used for this type of research need to be provided.

It is proposed that future researchers doing this type of work should publish more information about their intermediate data processing, filtering, and manipulation steps, as well as the underlying assumptions went into their calculations. This will help facilitate a conversation about what techniques are best to analyze vehicle fleet tracking data by providing

more information and improving transparency. It is hard to determine what different methods could be in use when there is no published information about these techniques.

Further evaluation and development of the data analysis methodologies presented in this thesis is also recommended, so the confidence in future scientific results can be improved. The next chapter (Section 7) provides a list of future work that could be completed to improve the confidence in and the accuracy of the final results produced by the data analysis methodologies presented in this thesis. Many of the additional steps listed in this next section address the potential concerns listed here about the validity of the results.

SECTION 7

FUTURE WORK

This work has raised additional questions. For example, is the presented data analysis methodology even valid? Or is using real-world vehicle fleet tracking big data really the best approach to answer questions about fleets of vehicles? Below is a list of future work that, in my opinion, could be taken to further advance the work presented in this thesis.

1) A sensitivity analysis should be conducted on each individual data processing and filtering step to determine how much a change in any individual step can affect the final results. This could be done in potentially two different ways, depending on the data processing or filtering step:
    a. Remove the data processing or filtering step if possible and rerun the analysis to see how the results change when that step is missing.
    b. If the filtering step depends on a numeric parameter, such as a SOC cutoff limit for the CD / CS drive mode transition, vary that parameter in both the positive and negative directions and then rerun the analysis.
2) Test the data analysis methodology presented in this thesis on additional datasets to see if it creates similar or different results. This will accomplish a few different objectives:
    a. It will check if the methodology continues to be robust on different datasets collected from different vehicle platforms and data collection systems.

b. It will help identify which data-processing steps are specifically needed for only the Odyne dataset and which data-processing steps are more universal to all vehicle fleet tracking data.
c. It will help identify new data filtering steps that are needed for errors that are not present in the Odyne dataset but are common in other similar datasets.
d. It could help identify unknown biases in the Odyne dataset and vehicle usage that could be influencing the final results. It is not guaranteed that the Odyne fleet represents the average usage of medium-duty utility work trucks.

3) Continue to develop the foundational software to process this kind of vehicle fleet-tracking data. A more detailed list of software changes is presented in Subsection 2.4. Although additional software development work will postpone the work to answer additional research questions, building a stronger foundational toolset to manage this type of data will also benefit this future work when it is conducted. See Appendix A.7 for a longer discussion about what should be considered when choosing a data management framework and/or data analysis software. Some of the perceived advantages and disadvantages of using both the custom MATLAB framework and Hadoop MapReduce on the EPRI dataset are discussed in the appendix.
4) Final results, such as drive and charge event summaries, should be verified independently using other data and/or methods.

a. For example, a first step would be for a dedicated researcher to drive an Odyne or Via truck around for a few days and meticulously record all of their driving and vehicle usage in a paper log similar to the NHTS survey. Then data from that vehicle's CAN system could be run through the algorithms to see if the results were in agreement with the manually recorded driving log. Unfortunately, CSU did not have physical access to any of the Odyne or Via trucks so we could not perform the work here ourselves.

b. An alternative method would be to try and calculate some of the same results using different CAN signals. For example, vehicle Odometer could be used to verify that speed integration was producing a reasonable distance results. Section 3 can be referenced for ideas about different signal combinations that could have been used to answer some of these questions.

5) The software could be re-written from scratch by another programmer based on the process and algorithms outlined in this document. If the new software gets the same results it will help verify that there are no "bugs" in the original analysis software that was created here at CSU. Or if this algorithm is used on a new dataset, it is highly recommended to pursue two independent software development efforts to implement the algorithm if there are enough resources and people available to do so. This will help validate the final results and reduce the risk of a software bug. Unfortunately, due to the limited time and funding here at CSU, we were only able to write one version of the software that we used for this project.

6) Additional data processing and filtering steps could be added on top of what has already been outlined in this document. There may be other vehicle-tracking datasets with other errors or problems that require a different approach. CSU implemented as many data-processing and filtering steps as time and resources permitted, but there are likely additional undiscovered problems in the EPRI Commercial Truck dataset that are not being addressed.
7) The data-processing steps presented here could be optimized to reduce the computer processing power and the time required to generate results. For example, maybe some of the data processing steps could be reordered in a way that does not affect the final results but reduces the computational run time. The main focus of this study was to generate an algorithm that produced meaningful and accurate results, not a fully optimized algorithm that ran as quickly as possible. Although some optimization was implemented into our software as convenient, this was not the primary focus of the software development effort.
8) An effort should be made to understand why the Via dataset is reporting significant fuel usage when Via is supposed to be driving in an all-EV Charge Depleting mode (see Subsection 5.5.6). In addition, more work to understand the effects that ambient temperature has on the efficiency of an all-electric powertrain is recommended in general.
9) An updated version of this vehicle fleet-tracking big data analysis methodology should be published if some of the future work recommendations outlined here are implemented. CSU believes that there should be a vehicle-fleet data analysis "cook book" that describes all of the methods that can be used to analyze and process this

kind of data. An entire book could easily be written about the subject and it will likely need to be very lengthy as this kind of data analysis is highly complex and nuanced. We welcome future research that builds upon what we have published in this thesis.

Finally, I would like to say that everyone on my team (all previously mentioned in the Acknowledgements section) worked very hard on this project. We did the best job we could to develop these data-analysis methodologies as much as possible with our available resources. However, a complete effort to fully implement all of the future work recommendations outlined above would likely be a very large undertaking. It would likely require a large team of researchers, a large budget, and more time. Although these resources were not available here at Colorado State University for this thesis, it is our hope that we have provided a starting point for this type of larger project in the future. One of the main goals of this work is to start a conversation, not to provide answers for every open question that was raised by this research.

CONCLUSION

This thesis has defined and completed a series of tasks to address the primary research challenges associated with the collection, processing, and analysis of large datasets from the CAN systems of PHEV's operating in real-world conditions. The primary contributions of this thesis are presented below:

- A documentation and description of the analysis methodologies, assumptions, and intermediate data processing steps for constructing vehicle fleet-tracking big data analysis software.
- A synthesis of the research questions available, the challenges, and the requirements associated with answering those questions on the basis of transportation fleet "big data."
- A case study of the collection, processing, validation, and analysis of big-data collected from PHEV's in real-world operation.
- Sample results from our data processing software, including but not limited to: utility factor curves, fuel economy, and a correlation between the fuel economy and ambient temperature.
- The medium-duty truck utility factor curves and the correlation between ambient temperature and fuel economy for a mild-hybrid medium duty truck are unique and have not been previously published.
- The assumptions and uncertainties behind the data-analysis methodologies and results presented in this thesis are discussed.

- A list of open questions that need to be resolved and future work that needs to be conducted to improve the confidence in the results from this type of data analysis is presented.

It was demonstrated in Section 6 that different data-analysis methodologies and intermediate data processing steps can influence final results. One major contribution of this work is that it completely outlines the data analysis methodologies used to produce final results so the methods can be further developed, validated, and defined in future work. In addition, some of the software used to produce these results was described.

A list of potential research questions was compiled and approaches to solving the problems were theorized in Section 3. One important challenge in fleet data analysis is identifying the appropriate CAN signals and methods that are needed to answer certain research questions, so this list should provide a starting point for future research projects. A subset of the reviewed questions was later answered in this thesis.

A methodology for generating a summarized list of driving and charging events from second-by-second fleet data was developed and presented in Section 4. The drive-event results were then used to generate utility factor curves for the Odyne and Via truck fleets as well as other statistics of interest. These utility factor curves are the first that have been published using medium-duty truck data, so the results are unique.

Another methodology was developed to discretize the continuous-driving data from a drive event into approximately 90-second driving intervals so a regression model could be plotted. This methodology was presented in Section 5. Sample results, such as the correlation between ambient temperature and fuel economy, were also presented. These results from the

mild-hybridized Odyne truck are similar to the ambient temperature vs. fuel consumption trends seen in conventional vehicles. However, as the HVAC system was not frequently used in the Odyne trucks, these results could be different if HVAC use was different.

The importance of using this kind of real-world vehicle tracking data was demonstrated in Subsection 6.2 by showing:

1) How the real-world fuel economy can differ from the fuel economy calculated on EPA drive cycles.
2) How the real-world utility factor can vary from the standard utility factor curve based on different subcategories of vehicle.

In addition, real-world data can identify trends that may not exist in a controlled laboratory experiment and it can prevent companies from cheating on EPA drive cycle tests. These benefits are also discussed in Subsection 6.2.

However, potential pitfalls of using real-world vehicle big data are also presented and the uncertainties and assumptions behind the results presented in this document are also discussed in Section 6. More work is needed to better define the methods and feasibility of using this kind of vehicle fleet tracking big data and a list of future work recommendations is presented in Section 7.

Overall, this work provides a detailed description of the data analysis methodologies used to process and analyze vehicle fleet-tracking big data as well as sample results that show real-world applications for this type of analysis. The hope is that this thesis can help start a conversation about what data analysis methodologies are considered to be the "best-practice" so future researchers can generate better results from vehicle fleet-tracking data.

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APPENDIX A

GENERAL CONSIDERATIONS FOR COLLECTING AND ANALYSING VEHICLE FLEET-TRACKING DATA

Although the discussion in this appendix is not central to the research objectives and conclusions presented in this thesis, it offers some generalized advice and considerations to anyone thinking about collecting and analyzing data from a fleet of vehicles. Topics include how to interpret data, potential glitches in the data, privacy and security considerations, etc. This appendix is not meant to provide complete solutions to all of these issues, but instead intends to make future researchers a high-level awareness of potential challenges that may be faced.

A.1 Information Reported by the Onboard CAN System May Not Be Entirely Accurate

First of all, a major challenge is discovering any potential flaws in the dataset as there can be unknown glitches and errors in the manufacturers CAN system configuration. Since collecting data from CAN systems for entire vehicle fleets is a relatively new practice, unknown bugs in the CAN system are often discovered when extremely large quantities of information becomes available from the system. Many OEM's likely do not test their CAN systems with the quantity of data collected from real-world fleet tracking. For example, during this project EPRI and its contractors would often follow up with the vehicle OEM's to report bugs that were found in the CAN system data and try to get them resolved to improve future data collection efforts. That is likely a full time job just by itself, so we are thankful that EPRI

and its contractors had the resources to do this kind of work outside of Colorado State University.

A.2 Additional Background Information, Sometimes Proprietary, Is Needed to Interpret the Raw CAN System Data Collected from Vehicle Platforms

Next, information about what exactly the different CAN signals are is needed so they can be decoded and interpreted. Some of this information is available in lengthy engineering standards such as the SAE J1939 [23] and ISO 15765-2 [24] standards, while other CAN signals require proprietary information that is specific to individual vehicle platforms. Information may be needed from the manufacturer to properly configure the system for manufacturer specific CAN signals. EPRI and its contractors performed much of this work and a team of people is likely required just to figure out how to collect data from the CAN system. When the CAN signals are recorded, information about the signal units, data collection rate, and a description about what each CAN signal measures is also needed. Most CAN signals are labeled with hexadecimal PID keys when they are read directly from the vehicles CAN-communication bus, so these should be mapped to text string labels that are more human readable such as "vehicle speed."

A.3 Fleet Data Often Has a Time Dependency, So It Often Needs to Be Processed in Time Order

Another challenge to analyzing vehicle fleet data is that much of the data is time dependent, so computations often cannot just occur in a random order when the data runs on something like the Hadoop framework where by default data is read and written in a random

order. The data often needs to stay sorted in a time-sequential order so the time dependencies can be observed.

As the data grows larger, it may be necessary to split up this sequence of events into multiple files for memory management. However, if the data analysis script is looking for high-level events such as a vehicle trip, these trips may get split into two different pieces depending on how the splitting process works. Our process just tried to make the split sizes large enough that a few splits are unlikely to significantly impact results. Another approach that could have been used would have been to split the data files at midnight or early in the morning as vehicle generally are not driving during these times. Finally, a third approach might be to write software that remembers if the analysis was in the middle of a vehicle event at the end of the data file so it could then load the next consecutive data file and continue the analysis to see if the event continues. This last approach is likely the most accurate as it would remove the effect of the data splits. However, the last approach would also require much more sophisticated software to be developed, which increases cost and development time.

A.4 The Privacy of Individual Drivers in the Fleet Could Be Put at Risk

Since fleet-tracking data records the habits of individual drivers and their vehicles, privacy and security is another concern that must be considered. In many circumstances, all raw information collected from the vehicle needs to be protected from public disclosure. Timestamped GPS coordinates and VIN numbers are examples of especially sensitive information that could be abused the wrong hands. For example, maps can be created that track an individual's driving patterns and history as GPS is accurate enough to see exactly where and when the vehicle was driven or parked. Or, it would be possible to determine if an

individual is not following the speed limit or driving recklessly. None of our studies reveal any of this information publically, but if the data were hacked, stolen, misplaced, or transferred to a rouge third party, these types of data analysis are technically feasible. As the scale of data collection efforts increases, privacy and security risks also increase.

To combat some of these privacy concerns, any results published from this kind of dataset needs to be anonymized so it can never be traced back to an individual driver, owner, or vehicle without their permission. Aggregating the data from all drivers and creating fleet-level summary statistics that include all vehicles is an excellent way to anonymize data if there are a sufficient number of vehicles in the fleet. In addition, legal authorization is likely needed to collect this kind of information from a fleet of vehicles and drivers should at least be aware that their vehicles are being monitored. In our study, the vehicles were owned by utility companies and not private individuals, so this reduced some but not all of the privacy concerns.

In addition, it is strongly recommended that transportation fleet data is collected, transferred, and analyzed in a secure computing environment where the information is difficult for malicious third parties to hack, steal, and eavesdrop on. The specific security precautions implemented by Colorado State University, EPRI, and EPRI's contractors to protect the datasets used in our research will not be discussed in this document to protect our own security. However, it is strongly recommended that anyone who is attempting to collect, store, and analyze this type of data on a large scale should consult with a security IT professional to draft computer security requirements and precautions before the data collection begins. In general, everyone responsible for handling the raw or processed vehicle data should be aware of their specific responsibilities for protecting the data and keeping it secure.

It should also be noted that no computer security system can ever be perfect. Even if very strong computer security is implemented, it is probably impossible to ensure that all vehicle fleet data will always be 100% secure using current computing technology. Despite this, strong computer security precautions can still significantly reduce the risk of a data breech when collecting transportation fleet data.

When transportation fleet data is collected, these privacy and security risks need to be weighed against the other benefits of collecting this data so an informed decision about how to proceed can be made by project managers. However, it should never be assumed that there is zero risk of confidential data being stolen or accidentally published and it is recommended that risk management plans should be drafted.

A.5 The Security and Autonomy of the Vehicle CAN System Could Be Compromised by a Third Party

In addition to the privacy risks related to large-scale data collection discussed in the previous Appendix Section A.4, an addition security risk is the potential for vehicle CAN system hacking [73, 74]. Although it is unknown how great of a security risk this might pose as it is a relatively new risk and there are no known malicious examples of CAN system hacks, it is possible for an attacker who gains access to the onboard CAN network to take control of a vehicle, disable safety-critical systems, override driver input, disable the brakes, etc. [74]. When CAN networks were first built, they were isolated computer systems that required physical access to the vehicle in order to establish a connection. However, as more and more systems are networked onto the vehicle, it is now possible to access this CAN system remotely, but its original architecture was not designed with a potential cyber-attacker in mind. When

the CAN system of a vehicle is networked to a data collection system using the OBD-II port, similar to how the data for our studies was collected, it is theoretically possible for an attacker to infiltrate the data collection system and use that at an entry point into the vehicles on board computer system. Examples of CAN hacking to date have mostly been done in security demonstrations, as it is a relatively new security risk that is just now being understood.

How to understand and mitigate the risks of CAN network hacking could be the topic of an entirely different research paper or thesis. However, as the goal of this appendix is to give an overview of other considerations for fleet data tracking, this risk should at least be mentioned as it could become a greater risk in the future. Work could be done to make the internal CAN system of the vehicles more resilient to attack, or the existing CAN system could be placed behind strong firewalls so it is difficult to for an attacker to penetrate the fleet data collection system that is networked with the CAN system. Of course, as the scale of fleet-tracking data collection increases, the risks and consequences of a security breach will also increase.

A.6 Data Collected from Real-World Vehicle Tracking Systems Is an Observational Study, Not an Experimental Study

Any results collected from vehicle tracking systems are considered to be an observational study, not an experimental study. This is important, because it is generally much harder to establish a cause and effect relationship in observational data since it is not being collected from a controlled environment. Often, only correlations can be discovered in observational data. For example, our data can show the correlation between fuel economy and ambient temperature, but truly understanding the reasons behind these trends would most likely

require additional information from outside of the dataset. An experimental study on the other hand is performed in a controlled environment and generally only a single variable is changed at a time. Therefore, any other variables affected by that change in the experimental setup likely indicates causation.

A major challenge of interpreting the correlations found in vehicle fleet-tracking data will be to determine the underlying causes of those correlations, and that might be the harder part of the problem to solve. However, this does not mean that identifying correlations is not useful, as finding strong correlations can still provide clues about where to start looking next. They can also be used in predictive models.

A.7 Summary of Our Experiences Working With Different Data Management Software and General Considerations for Determining What Type of Software to Use

At the beginning of any data analysis project, one of the first decisions that need to be made is what type of data management framework and / or software should be used to process the data. In this work, both a custom MATLAB framework and Hadoop MapReduce were used for different pieces of the big data processing challenge and it was found that there were advantages and disadvantages to using both systems. Here is a list of some general considerations for choosing a data management framework and/or software to conduct data analysis on vehicle fleet tracking big data based on our experience:

1) It needs to be determined which data management framework is the best suited for the type of data being processed. For example, is the most ideal tool a custom MATLAB framework like the one described in this thesis, Hadoop MapReduce, or

some other big data management system? Although it is hard to answer this question without a better understanding of the specific data processing application, here is a list of our experiences using both MATLAB and Hadoop MapReduce for our project:

a. The custom MATLAB framework potentially offers greater flexibility and customizability than Hadoop. Writing your own software also gives you a deeper understanding of how the software works, so it can be easier to debug later on.
b. However, using a custom MATLAB framework also requires more software development work and it is hard to write custom software to the same high quality industry standards that a widely available framework such as MapReduce is developed to.
c. MATLAB offers some advantages in terms of processing time-dependent data as well, as it does not by default read in data points in a random order as MapReduce does. Data often must be maintained in chronological order to conduct vehicle fleet-tracking data analysis.
d. Java heap errors are another common problem encountered when using MapReduce software, so that is one of the reasons that MATLAB was first used in Section 5 to pre-split the data files in the Phase 1 processing step before the data was passed onto the Phase 2 processing step where MapReduce was used. It was unclear if a whole file input format could be used in the mapper stage with up to 1 GB CSV data files.

e. One advantage of MapReduce is that it already has a lot of useful features built into the framework, such as error tracking, parallelization, and fault tolerance that would have to be manually programmed into a custom MATLAB framework.

2) Depending on the data size, parallel processing may or may not be needed. Parallel processing offers many advantages in terms of much faster computation run times, but it also likely requires more computer hardware and software development time. MapReduce is already designed to run in parallel. MATLAB can be theoretically be programmed to run in parallel on a computer cluster [34, 35], but CSU did not spend much time implementing parallel MATLAB code.
3) The data analysis framework should have flexibility to adapt to different data formats and it should be easy to add new data analysis code into the framework without interfering with any of the data management code. Rapidly changing requirements and tight deadlines can be a challenge to any project and a flexible software design can go a long way towards relieving some of the pressures created by rapidly changing project requirements or input data formats.

Other commonly used big data management frameworks and tools that were not used for data analysis work at CSU are listed in *Section 1.5 - Overview of "Big Data" as a Concept Beyond Fleet Data*. These include Google File System [29], Tableau [31], NoSQL [31], Amazon Web Services [31], and Storm [31]. In addition, other programming languages such as R or Python could also be considered for this type of work [75]. Although some R was used in our work for post processing, this post processing only occurred when the data was in a

highly reduced final format where it probably can no longer be considered to be a big data problem.

Since big data is a relatively new and upcoming field, it is recommended that future researchers who are conducting this type of vehicle-fleet big data analysis perform their own research on big data processing frameworks and software at the beginning of their project. The commonly used commercial big data management frameworks listed in this document could become obsolete within even a few years and there could be other tools available to future researchers. Overall, the technology to process big data is rapidly advancing and the choice of a data processing tool at the beginning of a project can have a large impact on the final results and success of that project.

LIST OF ABBREVIATIONS

1Q – First Quartile (a statistical term)

3Q – Third Quartile (a statistical term)

A – Amps (unit of electrical current)

AC – Alternating Current (or see alternate definition)

AC – Air Conditioning

aka. – Also Known As

AWS – Amazon Web Services

BASF - Badische Anilin und Soda Fabrik (a German chemical manufacturing company)

BMW - Bayerische Motoren Werke AG (a German automotive OEM)

C – Celsius (unit of temperature – deg C)

CAN – Controller Area Network (commonly used on vehicles to network various sensors and processors)

CD – Charge-Depleting (Drive mode where battery is losing charge. Also see alternate definition of CD.)

CD – Current Directory (alternate definition)

CDMA – Code-Division Multiple Access (radio transmission technology commonly used in cell phones)

CILCC – Combined International Local and Commuter Cycle

CS – Charge-Sustaining (drive mode where battery charge is maintained)

CS – Computer Science (alternate definition)

CS435 – Course Number for Big Data Analysis class in the Computer Science Department at Colorado State University in Spring 2016

CSU – Colorado State University

CSV – Comma-Separated Values (common file format for data storage)

DC – Direct Current

deg – Degrees

DF – Degrees of Freedom (a statistical term)

DFS – Distributed File System

Dr. - Doctor

EPA – U.S. Environmental Protection Agency

EPP – Emerging Professionals Program

EPRI – Electric Power Research Institute (sponsor for this research)

EV – Electric Vehicle

EVS29 – Electric Vehicle Symposium 29

F – Fahrenheit (unit of temperature – deg F)

FC – Fuel Consumption

FCCC – Freightliner Custom Chassis Corporation

FE – Fuel Economy

ft – feet (English unit of distance)

FTP – Federal emissions Test Procedure

FUF - Fleet Utility Factor

gal – US Gallons (English unit of volume)

GB – Gigabyte

GMT – Greenwich Mean Time

GPS – Global Positioning System

GSM – Global System of Mobile communications (radio transmission technology commonly used in cell phones)

HDFS – Hadoop Distributed File System

HEV – Hybrid Electric Vehicle

HHDDT – Heavy-Heavy Duty Diesel Truck

hr – Hours (unit of time)

HVAC – Heating, Ventilation, and Air Conditioning

ISO – International Standards Organization

IT – Information Technology

KI – Kinetic Intensity (see citation [46])

km – Kilometers (metric unit of distance)

kph – Kilometers per Hour

kW – Kilowatt (unit of power)

kWh – Kilowatt Hour (unit of energy - generally used to measure electrical energy)

.mat – MATLAB data file format

MATLAB – Matrix Laboratory (a numerical computing environment and programming language)

MB – Megabyte

mi – Miles (English unit of distance)

min – Minutes (unit of time)

mpg – Miles per Gallon

mph – Miles per Hour

MS – Microsoft

N/A – Not Applicable

NHTS - National Household Travel Survey (a government sponsored survey of driving behavior in the United States [47])

NREL – National Renewable Energy Laboratory (U.S. Department of Energy Facility)

NoSQL – Not Only SQL

OBD (and OBDII) – On Board Diagnostic system

OCTA – Orange County Transport Authority

ODY - Odyne

OEM – Original Equipment Manufacturer

PHEV – Plug-in Hybrid Electric Vehicle

PID – On-Board Diagnostic Parameter ID (a hexadecimal key that identifies unique signals in vehicle CAN systems)

Pr(>|t|) – p-value for a t-test as notated in R-console output

QQ-Plot (or Q-Q Plot) – Quantile-Quantile Plot

R – A statistical programming language

RAM – Random Access Memory

RCD – Range Charge Depleting

RPM – Rounds per Minute (rotational speed)

R-squared – a statistical measure (not to be confused with R)

SAE – Society of Automotive Engineers

sec (or secs) – Seconds (unit of time)

SOC – State of Charge (% charge level of the primary battery in an electric vehicle)

SQL – Structured Query Language (a computer database language)

UF – Utility Factor

US – United States (of America)

V – Volts (unit of electrical voltage)

VIN – Vehicle Identification Number

vs - Versus