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Developing A Real-World Vehicle Trip Dataset Through Public Travel Surveys And Applying It To Battery Electric Vehicle Performance Study

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DEVELOPING A REAL-WORLD VEHICLE TRIP DATASET THROUGH PUBLIC TRAVEL SURVEYS AND APPLYING IT TO BATTERY ELECTRIC VEHICLE PERFORMANCE STUDY

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DEDICATION

I dedicate my humble work in this dissertation to my father and mother who encouraged and supported me during all of my life to be a successful person, to my wife and children who struggled and continued to support me to achieve our goals, to all my family members and friends who encouraged and helped me finish my dissertation, and to all people and the community in my village and hometown.

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INTRODUCTION

1.1 Problem Statement

1.1.1 Need of Creating a New Second-by-Second Trip Dataset

Improving vehicle fuel economy is a crucial part of international and regional efforts to reduce the risks of climate changes and global warming. Transportation sector is responsible for 29% of total US greenhouse gas (GHG) emissions and accounted for 28% of total US energy use. Light-duty vehicles are responsible for 59% of transportation sector GHG emissions and accounted for 54% of total US transportation energy use [1], [2]. The quantity of automobiles in the U.S. increases each year [3], and thus, petroleum utilization increases and vehicle GHG emissions increases as well. Vehicle GHG emissions cause major environmental problems. In this way, environmental issues require vehicles with high fuel efficiency and low gas emanations. Additionally, the reliance on oil and the fluctuating fuel prices motivate automakers to develop vehicles with low fuel consumption.

Considering vehicle consumer's point of view, consumers put significant weight on fuel/battery efficiency and cost [4]. In the US, consumers rely on a vehicle window sticker that shows vehicle's estimated fuel economy in miles per gallon (mpg) from the Environmental Protection Agency (EPA) [4]. This figure is produced by automaker's laboratory tests and is regulated by federal laws. The fuel economy tests are performed in a laboratory using a dynamometer. They are based on controlled conditions using up to five standard EPA drive cycles to simulate standard vehicle trips in different environments. Table 1 shows some of EPA and European standard drive cycles and cycle procedures that are used in fuel economy and vehicle emissions tests [5], [6]. The EPA standard excludes

Table 1.1. EPA and some of European standard drive cycles and procedures used for dynamometer fuel economy and emissions tests.

Name	Description	Distance (miles)	Average Speed (mph)
UDDS	Urban Dynamometer Driving Schedule - EPA city cycle	7.45	19.59
FTP-75	Federal Test Procedure - EPA city cycle (EPA75)	11.04	21.20
US06	EPA high acceleration aggressive driving schedule	8.01	48.37
SC03	EPA Air Conditioning driving schedule	3.58	21.55
HWFET	EPA Highway Fuel Economy Driving (HWFET) Schedule. It represents highway	10.26	48.30
Artemis Urban	European Artemis (Assessment and Reliability of Transport Emission Models and Inventory Systems) urban driving schedule	3.03	11
Artemis Rural	European Artemis rural driving schedule	10.74	35.74
Artemis Highway	European Artemis highway driving schedule	17.86	60.22

some known on-road factors that affect fuel economy for the purpose of improved test repeatability. These factors include road and weather conditions, traffic, driving style, and geographical locations [7], which are difficult to model accurately. After auto manufacturers report their results to EPA, the agency reviews the results and checks about 15%–20% of them through its own independent testing [8]. It has been reported that the on-road fuel economy can be markedly lower than the window sticker number, which has happened to conventional vehicles as well as to hybrid electric vehicles (HEVs) [9]. To improve the accuracy of the lab tests and to better evaluate new technologies' potential impact on the fuel/battery usage, automakers desire to incorporate a broader range of the real-world factors into their testing, analysis, and estimates. In order to achieve improved fuel economy estimates of on-road driving, a large set of on-road vehicle and trip-related data must be used. A project solely dedicated to generating such a dataset can be prohibitively expensive and time-consuming to execute.

Few options remain. One of them is to utilize vehicle travel survey data. Various vehicle fuel consumption models have been developed based on historical data collected from self-reporting travel surveys. The historical data is affined to the vehicle itself. Some types of this data, for example, are vehicle type and model, engine type, number of cylinders, transmission system type, horsepower, vehicle weight, displacement, and acceleration [10]. Despite the fact that the proposed techniques using historical data have been found to have good capabilities and reliability in predicting fuel consumption, they cannot represent the effects of driving patterns because they lack GPS data besides the lack of accuracy in the self-reporting trip-related data such trip distance and duration. It is difficult to extend the predictions to cover new technologies because the characteristics of the new vehicles, such as start/stop, hybridization, and heat recovery, can cause significantly different powertrain behavior. Therefore, more accurate and effective trip-related data with high-resolution must be included in fuel economy studies to achieve better estimation results. These requirements can be achieved by using the GPS techniques in travel surveys. An important step was taken towards improving travel survey methods by introducing GPS-enhanced travel survey techniques [11]. Hence, a significant direction in fuel economy studies is to use the data collected by these GPS techniques to achieve accurate results. The use of GPS data collection has been found to have many advantages, such as data accuracy, over traditional survey methods. The data collected can include trip distance, duration, average speed, and maximum speed besides time-speed points [11]. Numerous travel survey datasets are available to the public by various providers and organizations. Several studies have used this type of datasets to enhance vehicle fuel economy. However, the collection period for the GPS data in most of the studies in the literature, to the best of found knowledge, is short (compared to the period of the year) for a comprehensive fuel economy or battery life study. To efficiently study vehicle fuel economy/battery life, the used travel survey dataset should include year-long driving and none driving activities of a large group of vehicles and drivers along with their second-by-second GPS data. Using this type of datasets ensures that all real-world factors and conditions in all different circumstances and seasons that influence vehicle fuel economy/battery life throughout the entire year are taken into the account. Road and weather conditions, driving style, and geographical locations are examples of these factors. Furthermore, the on-road drive cycles collected in travel surveys include more aggressive acceleration and deceleration activities than the drive cycles used in laboratory tests and this affects vehicle performance.

Such a long-period and high-resolution travel survey dataset is not only necessary for efficient fuel economy/battery life studies, but also required in some other transportation studies such as vehicle greenhouse gas emissions and travel behavior and demand studies. Both GPS and household data collected in travel surveys have been found useful to study vehicle gas emissions and travel behavior and demand [12] – [15]. GPS data collected in vehicle trips are powerful for exploring and estimating vehicle instantaneous emission rates and study travelers' behavior and pattern. However, the two transportation studies strongly depend on several seasonal factors such as weather, especially the ambient temperature, that significantly change during the year and affect the driving pattern [16], [17]. Hence, to efficiently study and analyze vehicle gas emissions and travel behavior and demand using the on-road data collected in travel surveys, the used travel survey dataset should include vehicle trips made in a minimum period of one-year along with their GPS second-by-second speed profiles so that all circumstances and impacts that influence vehicle gas emissions and travel behavior and demand throughout the year are taken into the account. Nevertheless, there is no study in the literature has used such a dataset to analyze and explore vehicle gas emissions and travel behavior and demand for a one year period.

From the above, it can be summarized that to achieve batter and more reliable and realistic results in transportation studies, such as fuel economy/battery life, vehicle emissions, and travel behavior and demand, a large long-period dataset that includes real-world vehicle trips along with their second-by-second driving cycles GPS data and parking activities is obviously required. To the best of author's knowledge, this type of vehicle trip dataset is not available in publicly accessible databases and a project specifically dedicated for generating such a type of dataset can be excessively expensive and time-consuming to be executed.

Hence, the aforementioned reasons and others, gave me high motivations and challenges to perform my research and develop a method that utilizes two public travel survey datasets to generate such a dataset that may contribute to the fields of ongoing transportation research studies. The US National Renewable Energy Laboratory (NREL) makes some travel survey datasets of passenger vehicles accessible to the public [18]. Among them are the Puget Sound Regional Commission (PSRC) and Atlanta Regional Commission (ARC) travel survey datasets. The two datasets included different types of passenger vehicles, such as sedans, mini-vans, pick-up trucks, and sport utility vehicles. The PSRC is the only dataset provided by NREL that covers customer full driving operations for a period over one year with full detailed trips including the accurate start/end of trip, soak time between trips (the time length between the end of a trip and the start of the next trip), and actual trip distance and these are among the reasons to choose the PSRC dataset for my study. The higher resolution and the longer period of the GPS data collection (compared to the datasets provided by NREL), less data errors, and the larger number of vehicles are among the reasons that we chose to use the ARC dataset as the source for the second-by-second trip drive cycles.

1.1.2 Need of Studying Battery Electric Vehicle (BEV) Performance and Utilization Using the Proposed Second-by-Second Trip Dataset

Tremendous efforts have been made by governments, automakers, and public organizations to reduce the GHG emissions caused by light-duty vehicles and their use of petroleum energy. Among these efforts are the improvements and enhancements of the Battery Electric Vehicles (BEVs). BEVs are zero emission vehicles and they may significantly contribute to solving air pollution problems. BEVs have become of more interest to automobile drivers and their sales obviously increased in the last few years worldwide and in the US [19], [20]. BEVs sales worldwide increased from 1,224,000 vehicles in the 2017 to 2,018,247 vehicles in the 2018 and 361,307 of them were sold in the US [20]. However, BEVs contribute with only about 1% of the US total transportation [3]. Several issues with BEVs are still causing concerns for drivers to adopt a BEV and may be the most important issue is their limited range – the distance traveled by a BEV per one full battery charge. People fear of not getting to their destinations and being stranded on the side of the road because the battery has become empty. Also, drivers wonder about adapting their driving behavior and activities if they decide to displace their conventional vehicles with BEVs. Other issues include the battery recharging time and electrical energy consumed. These issues encourage researchers and engineers to study and analyze the BEVs.

Several research studies analyzed and examined the range limitations and requirements of BEV. Most of these studies used trip's data collected from conventional passenger vehicles in travel surveys. A group of these studies are only based on testing the daily traveled distance against some fixed distance threshold, which is the range of an average BEV at the time of study. The studies do not include second-by-second drive cycles and some other main factors that influence the performance of BEV such as the ambient temperature and climate control system [21]. Studies such as in [22] and [23] show that the performance and range of BEV significantly depend on driving and environmental factors such as the driving pattern/behavior, ambient temperature, and climate control auxiliary energy consumption associated with the ambient temperature. Consequently, to better study and analyze the range and performance of BEV, some studies considered the impact of ambient temperature and used temperature data besides the data collected from travel surveys and some other studies additionally included the second-by-second drive cycle profiles of trips to consider the effect of driving pattern and aggression. Nevertheless, none of the studies in the literature that included temperature data and drive cycle second-by-second data has performed a simulation using a year-long dataset that includes trips made by the same group of vehicles and drivers along with their second-by-second speed profiles throughout an entire year.

Additionally, most of the studies in the literature assume that vehicles are fully charged once daily overnight at home and this may not be true if we consider the daily life of customers throughout the year. Drivers may travel in vacations and may not be able to charge at their temporary place of residence at night. Also, it is not always true that customers stay home at night for enough time to have the battery fully charged. On the other hand, besides the night charging, drivers may tend to charge their battery at home during the day time if they intend to stay home for relatively a long period. Consequently, customers' daily life and activities should also be included in the analysis of BEV utilization and performance to achieve realistic results.

Hence, to efficiently simulate a BEV model and more accurately analyze and estimate its real-world performance and range limitations through the entire year, the simulation study must take into the account all of the factors that influence the performance and utility of BEV during the year and this can be accomplished by using a trip dataset that includes one-year worth of trips of conventional passenger vehicles and their second-by-second velocity profiles besides the annual data for ambient temperature. Additionally, the used dataset should include information and details about the destinations of trips and tours that drivers took throughout the year where such information should be considered in battery charging scenarios to simulate the actual drivers' life activities.

As a result, because the dataset I generated in the first part of this dissertation includes all of the above mentioned requirements for such a dataset for more efficient study of BEV utilization and performance during the entire year, I was motivated to study and analyze BEV performance and utility using the generated dataset as the source for vehicle trips and their second-by-second driving cycles, the Advanced Vehicle Simulator (ADVISOR™) software as a simulation tool, and the 2018 Nissan Leaf as a representative of recent BEVs.

1.2 Literature Review

The main objective of this section is to review the studies in the literature that are related to my work and highlight their shortcomings. The first part of this section covers the literature review of vehicle fuel economy, vehicle emissions, and travel behavior and demand studies. Also, the first part reviews the studies in the literature that used the two travel survey datasets that used in my study (i.e. PSRC and ARC datasets) for different applications. In the second part of this section, the studies in the literature that used vehicle travel surveys data to study the performance and utility of BEVs are reviewed.

1.2.1 Research Using Travel Surveys in Fuel Economy and Other Transportation Studies

In addition to the test procedures for vehicle fuel economy that are designed and certified by EPA and some other related organizations, several researchers and automakers proposed different techniques and methodologies to estimate and predict vehicle fuel consumption based on different types of data collected from real-world travel surveys. Using the real-world data in fuel economy studies accounts for and reflects the real terms and factors that may influence the fuel consumption. These factors might include, for instance, road and weather conditions, driving style, traffic, and geographical locations. Additionally, compared to the standard driving cycles used in the certifying lab procedures, the real-world travel survey drive cycles include more aggressive acceleration and deceleration activities and this significantly influences vehicle performance and its efficiency in fuel consumption.

Various vehicle fuel consumption models have been developed based on historical data collected from self-reporting vehicle travel surveys. For example, studies in [24] – [26] develop fuel prediction models that are totally based on vehicle historical data using the regression modeling approach and the neural network approach. The proposed models showed reasonable fuel economy predictions. The study in [27] also proposes a fuel economy estimation model based on the historical data using fuzzy c-regression models. Although the proposed techniques using historical data have been found to have good capabilities and reliability in predicting fuel consumption, they cannot represent the effects of driving patterns and aggressions because they lack GPS data. It is difficult to extend vehicle fuel prediction models based on historical data to cover vehicle new technologies because the characteristics of the new vehicles, such as start/stop, hybridization, and heat recovery, may cause different powertrain behavior.

Because of the improvements made in vehicle travel surveys by introducing the use of GPS technologies, fuel economy studies tended to use the data collected by these GPS techniques besides other travel surveys data. Numerous travel survey datasets are available to the public by various organizations and providers. Several studies in the literature have used this type of datasets to study and improve vehicle fuel economy. For instance, in [28] GPS data collected over a 24-hour period is used to study the influence of real-world drive cycles on plug-in hybrid electric vehicles (PHEV) fuel efficiency and cost for different powertrain and battery characteristics. In [29], data collected in California from 422 vehicles within seven days using in-vehicle GPS devices is used to predict fuel economy by customizing on-road drive cycles of the dataset. In [30], one-day long GPS driving cycles for 783 vehicles operating in Texas are used to simulate and study the performance of different vehicle powertrains. Using the same dataset, chances of increasing fuel savings by adapting the on-road drive cycles based on some standard levels of acceleration rates and cruising speeds are studied in [31]. In [32], the data collected in a GPS-based travel survey is used to obtain a large set of real-world drive cycles from 227 vehicles in 24 hours with second-by-second time resolution in St. Louis metropolitan region. The study use the GPS data to investigate the performance of different vehicle technologies. The study in [33] investigates the impact of on-road driving cycles on PHEVs using the GPS data from Southeastern Michigan collected from 11 vehicles in 26 days. However, we highlight that the maximum collection period for the GPS data in the above studies is only 26 days, which would be too short for a comprehensive fuel economy or battery life study that needs to cover conditions in different circumstances and seasons throughout an entire year.

From the above review, we can summarize that all mentioned methods used one of two techniques to study vehicle fuel economy using travel surveys. One technique is based on using the real-world variables that are directly related to the driver and/or the vehicle in the real life and it lacks the data and information of second-by-second drive cycles. The other technique is based on the use of the publicly available travel survey datasets that include GPS data. Nevertheless, none of the researches have used the GPS data for a long-term study. The short time-period of the data samples leads to the lack of account for the use of year-long real-world data and the various seasonal and environmental conditions that impact vehicle fuel economy. Accurate prediction of the widespread, real-world use of vehicles demands large data sample size that covers the entire year and therefore the various seasonal conditions and factors are involved.

Another important application of GPS-enhanced travel surveys is to study greenhouse gas emissions. For instance, the study in [34] use the GPS data collected from over 15,000 taxi vehicles during two weeks to predict air pollution and emissions from vehicles in Singapore. A model was implemented to predict the microscopic emissions of carbon dioxide (CO_2), nitrogen oxide (NOx), volatile organic compounds (VOCs) and total suspended particles. The model was based on the velocity and acceleration parameters determined from the GPS data. In [35], the GPS data collected in one week were used besides the traffic density and CO_2 concentration data to construct an estimation model that could infer and predict instantaneous emission rates. However, the collection period of the GPS data used in most of the studies in the literature is short, for example two weeks as in [35].

The GPS-enhanced travel surveys are also used in travel behavior and demand studies. For example, the study in [36] combined GPS data with Geographic Information System (GIS) to observe and explore travel activity patterns and activity scheduling behavior. Another study in [37] used data collected from 78 vehicles in four weeks with the trip GPS second-by-second driving data to explore and study drivers' travel behavior and characteristics. However, the shortcoming with the used datasets is again the short period of GPS data collection.

Nemours of travel survey datasets of passenger vehicles were made publicly accessible by the NREL. The PSRC and ARC datasets are among these datasets. The two datasets were used by some other researchers for different applications. In [38], the researchers used both datasets to understand the effect of travel time on auto travel choices by developing a method to calculate observed trip-level and household-level reliability measures. In [39] the PSRC survey data was used to explore the relationship between the population and employment densities and CO_2 equivalent (CO_{2e}) emissions taking residential self-selection into the account while in [40] the ARC dataset was used to measure driving inconstancy.

1.2.2 BEV Performance and Range Simulation Using Travel Survey Datasets

Several research studies analyzed and examined the performance and range limitations and requirements of BEV. The majority of these studies used trip's data collected from conventional passenger vehicles in travel surveys. The first group of these studies were only based on testing the daily traveled distance against a fixed distance threshold, which is the range of an average BEV at the study time. For example, in [41], data collected from 484 gasoline vehicles are used to study the range requirements for BEVs to cover the needs of these gasoline vehicles' drivers and they show that BEVs can cover a considerable fraction of range besides using some other transportations. The study in [42] used trips' data collected from 255 households in one year to analyze the percentage of household driving needs that can be covered by plug-in electric vehicles and show that 50% of one-vehicle households and 80% of multiple-vehicle households can meet their driving needs by using a BEV with 100 mile range. Similarly, the study in [43] used two different travel survey datasets to investigate BEV range requirements for one-vehicle and multiple-vehicle households. However, because the range of BEV significantly depends on driving and environmental factors such as the driving pattern/behavior, ambient temperature, and climate control auxiliary energy consumption associated with the ambient temperature, several studies analyzed the performance of BEV considering the impact of these factors. The experiment in [44] carried out on-road tests on a 2015 Nissan Leaf and the results show that the range of the tested BEV decreased about 45% due to cold weather conditions. In [45], the study analyzes the impact of driving aggression besides the climate and battery temperature on the performance of BEV. Using predetermined aggression-dependent models, the study estimates the energy consumptions for every trip at three aggression levels (high aggression, normal aggression, and low aggression) based on its average speed. The study shows that aggression strongly affects the performance of BEV. The study in [46] investigates the effect of regional temperature differences on BEV performance. The study used a temperature dependent model that was developed using data collected from real-world trips made by a 2013 Nissan Leaf. The study shows that the range of BEV decreased about 36% in the Upper Midwest of the US (cold climate). However, the studies in [45] and [46] do not include second-by-second drive cycles for the trips. The trip aggression cannot be accurately calculated without referring to trip GPS velocity profile.

To more efficiently study and analyze the range and performance of BEV, the second-by-second velocity profiles should be included in the study besides the ambient temperature data. The study in [47] sets an example in that direction. It simulates the trips of the 2009 NHTS with the use of second-by-second drive cycles from other travel survey datasets to investigate the capability of BEV to meet the range needs at 12 cities around the US. The study shows that 87% of vehicles driven on a given survey-day can be replaced by the representative BEV. However, the study does not estimate the energy consumption on second-by-second bases as the ADVISOR™ simulator does, rather it uses the GPS data to estimate energy per distance coefficient so it can be used with trip distance to estimate trip energy distribution. Also, some of shortcomings of the 2009 NHTS dataset are that the time of trips is not specifically provided as in PSRC dataset and the trip distance was provided based on the self-reporting method which may encountered high errors. The study needed to apply a de-rounding procedure to estimate the actual trip distance. Also, in this study every vehicle was only surveyed on one day of the survey period and as a result, the annual results were only estimated based on the surveyed day. It is more efficient for the analysis of BEV performance and range to use trips that were made by the same vehicles and drivers throughout an entire year of life. Furthermore, most of the aforementioned studies assume that vehicles are fully charged once daily overnight at home and this may not be true if we consider the daily life of customers throughout the year.

1.3 Research Objectives

The first objective of this study is to use the PSRC and ARC public travel survey datasets to produce a new and more efficient year-long dataset of vehicle trips and high-resolution driving profiles from the two datasets. NREL performed some data cleansing and error correction procedures to the raw data of both travel surveys. However, I found data errors in some sections and missing data in others, especially in the PSRC dataset. Therefore, I first aim to analyze and eliminate GPS-related data problems as exemplified by location drift and signal drop-outs that can cause errors, missing values, and inconsistency. I aim to develop error-correcting algorithms for both datasets. After the analysis and error-correcting steps, the goal of this study is to develop procedures to match the trips of PSRC vehicles to the trips of ARC vehicles using some key data variables such as trip distance and average speed. The resulting dataset contains trips with second-by-second drive data representing each trip made by the PSRC vehicles during one year period.

The objective of the second part of this work is to utilize the dataset generated in the first part of this work for studying and analyzing the performance and utility of BEV in a period of one year. I aim to use the developed dataset that includes one-year worth of trips of 382 passenger vehicles and second-by-second velocity profiles of the trips as well to simulate a model of a recent BEV and more accurately analyze and estimate its real-world performance and range limitations through the entire year. In addition to the long period of time and full detailed trips, the generated dataset includes information on the destination of every trip and the tours that drivers took throughout the year and my goal is to use such information for the simulation of a realistic strategy for battery charging and warming during parking events. This study aims to use the ADVISOR™ software to model a representative BEV and simulate the driving activities of every vehicle in the trip dataset throughout a period of one year in six different US cities to generate diverse ambient temperature profiles in different climates. Los Angeles, Atlanta, Phoenix, Seattle, New York, and Minneapolis are chosen as the representatives of different climates around the US. I aim to use the 2018 Nissan Leaf as the representative BEV. My goal is to develop an algorithm that draws trips' velocity profiles in the sequence provided by the travel dataset and ambient temperature data from the Typical Meteorological Year [48] database based on the simulated cities and calculates the energy consumption required by the Nissan Leaf on trip, daily, and annual bases. The algorithm also simulates the charging and non-charging time periods when the vehicles are parked. It calculates and monitors the battery temperature during these times based on the automaker's recommendations and suggestions. It also applies realistic assumptions and rules for the charging events based on the trip destination provided by the dataset. The charging strategy considers the manufacturer recommendations to charge more frequently in small amounts and keep the battery charge level as high as possible [49], [50]. The study aims to explore and analyze the performance of the modeled BEV during the activities of the simulated conventional passenger vehicles and the possibility of covering these activities by the simulated BEV throughout an entire year.

1.4 Innovative Technical Contributions

My proposed approach uses the PSRC and ARC datasets in a different and innovative way to introduce a method to generate a more powerful new dataset. The longer period of the PSRC survey captures driver variation encountered throughout the year. The ARC survey was run in a shorter period but had a second-by-second GPS resolution. The two datasets are complementary to each other and the new dataset generated by combining them can have both year-round trip representation and second-by-second drive cycle traces. The new dataset is more comprehensive than the other second-by-second datasets used in the literature for fuel economy and other transportation-related studies because it covers a full year. It represents not only the driving style of the driver, with respect to speed and acceleration of the vehicle, but also the trip patterns, including accurate times when the trips occurred and times when the vehicle is parked. It also includes detailed information about trips' destinations and tours. Such a dataset can be very useful and powerful in vehicle on-road researches such as fuel economy or battery life studies (as will be shown in the second part of this work), tailpipe emissions, and driving pattern and behavior analysis. My approach is innovative as no work in the literature has produced such a dataset. The dataset is ready to be used by vehicle drive cycle analysis tools, such as ADVISOR™. My approach can be generalized and employed to produce other realistic databases from other publicly available vehicle travel surveys.

In the second part of this work I introduce an innovative method to study and explore the utilization, performance, and range limitations of BEV during the entire year by simulating one-year of driving and non-driving activities of 376 vehicles of the innovative dataset I generated in the first part and taking into the account the real-world factors that impact the performance of BEV such as ambient temperature and climate control power. The proposed method is innovative where it simulates all of the vehicle one-year activities, including the driving cycles for every trip, in one second time resolution and to the best of my knowledge, none of the studies in the literature has performed such a simulation study. The study analyzes the performance of the modeled BEV during the activities of the simulated conventional passenger vehicles and explores the possibility of covering these activities by the simulated BEV throughout an entire year. Based on the simulation of the actual year-long vehicle activities, the study analyzes the required adaptions that customers need to consider when they decide to possess BEV. The study gives a helpful overview to automobile drivers about the performance of BEV and the challenges and obstacles that they may face throughout the year. My proposed approach can be extended to any type of BEVs and can use trips and vehicle activates from other vehicle travel datasets.

1.5 Dissertation Outline

The outline of the remainder of this prospectus proceeds as follows: Chapter 2 provides the methodology of the proposed technique to analyze and preprocess the two datasets and then match them to generate the new dataset. In Chapter 3, I present the results and findings of the procedures presented in Chapter 2. Chapter 4 presents my approach to simulate and study the performance of BEV and its utilization and range limitations using the dataset generated in Chapter 2. In Chapter 5, I reveal and discuss the results and findings of the simulation study presented in Chapter 4. Finally, Chapter 6 shows the conclusion and future work suggestions.

CHAPTER 2

METHOD FOR GENERATING A NEW Second-by-Second TRIP DATASET FROM THE PUGET SOUND REGIONAL COMMISSION (PSRC) AND ATLANTA REGIONAL COMMISSION (ARC) TRIP DATASETS

The first goal of this dissertation is to generate an enhanced high-resolution year-long travel survey dataset from the PSRC and ARC public travel survey datasets by applying several intensive analyzing and data-cleaning and validation procedures and then trips-matching algorithms. In this chapter all of the proposed procedures and algorithms applied to generate the new vehicle trip dataset are presented in details. The initial findings of the work demonstrated in this chapter was presented in a research paper [51] and the final study including all error-correcting and trip validation algorithms and matching procedures was presented in a second research paper [52].

2.1 Travel Survey Datasets Overview

2.1.1 Overview of PSRC Dataset

The Puget Sound Regional Council ran a travel survey between November 2004 and April 2006 to collect data with GPS devices from 484 passenger vehicles [53]. The data collection was a part of a pricing project sponsored by the Federal Highway Association [53]. The main objective of the project was to investigate the travel behavior diversities (numbers, modes, routes, and times of vehicle trips) in response to variable charges for road use (variable or congestion-based tolling) [53]. NREL makes a portion of the GPS survey data accessible to the public after handling the privacy issues [18]. The data provided by NREL is in raw format and may contain errors [18], [53]. The data is provided at the household and trip levels. About, 750,000 trips are available from 484 passenger vehicles reported over a period of 18 months (November 2004 – April 2006), and recorded more than 4.5 million vehicle travelled miles. The data contains 38 variables and among these variables are the actual trip distance, duration, average speed, and maximum speed [53]. The long time-period and the large number of trips make the PSRC dataset useful and powerful representing driver's vehicle usage patterns over a complete year or more. Another advantage of the PSRC dataset is the detailed information about tours and trips destinations. The trips of each PSRC vehicle are categorized by the original survey into four different tours: home-to-home, home-to-work, work-to-work, and work-to-home tours. The original PSRC travel survey also indicates if the a driver is in vacation [53]. This type of information about drivers' trip destinations and tours is useful and can be used in different transportation studies for several purposes such as studying travel characteristics and the strategy of charging the battery of the BEV, As discussed in Chapter 4.

2.1.2 Overview of ARC Dataset

The Atlanta Regional Commission conducted its travel survey to extensively study the residents' travel behavior and demographic characteristics within a study area that covers 20 counties in the state of Georgia [54]. The objective of this survey was to improve ARC travel demand forecasts. The survey was run during a two-month period (March-May and July-September 2011) to collect demographic and trip data from at least 10,000 households. Among this household sample is a subsample that includes more than 1,000 households that also included GPS data with a maximum of seven days of GPS data logging. 10,278 households completed the travel diary survey and 1,651 of these households completed the GPS part of the survey with about 40,000 trips [54]. The NREL concealed personal identification information and made the resulting datasets available to the public along with the raw GPS speed traces used to validate survey responses [18]. In addition to the survey results, NREL has applied a processing procedure to all vehicle GPS data to filter vehicle speed traces, and match vehicles to the streets of travel [18]. The NREL applied processing routines to process the travel survey data resulting in more than 350 data variables indicating the type of roads, drive cycle characteristics that incorporated the filtered speed and elevation, and trip type categorizations (home, work, school) when available [18], [54]. The vehicle sub-sample that submitted GPS data includes 1,653 passenger vehicles, 1,651 of which completed the processing and are included in the NREL-processed results. The quality and high time resolution of the data makes the ARC appropriate for second-by-second analysis using vehicle simulation models or other techniques.

2.2 Processing PSRC Dataset

2.2.1 Analysis of PSRC Data

Each of the datasets are analyzed to investigate their characteristics and determine their suitability for the intended study. In the analysis process, all the trips for every PSRC vehicle are investigated. The variables used are distance, average speed, maximum speed, and duration of a trip. These are the key variables in vehicle driving pattern and fuel economy studies that use travel survey data collected by GPS devices. They are also among data variables used by other transportation studies, such as vehicle gas emissions and travel demand and behavior. The distance-average speed relation is analyzed. Also, the distributions of average speed and maximum speed of all PSRC trips are analyzed. The PSRC vehicles that had trips in a period of one year or more are the focus of this study. A filtering and cleaning process is applied only to those PSRC vehicles that have such a one-year window. The filtering process comprises removal of trips with either zero distance or zero or negative duration, average speed recalculation, and maximum speed correction. Figures. 2.1 to 2.4 indicate that a pre-processing work is necessary. Figure 2.1 shows the distribution of the distance-average speed relation of the PSRC trips for the 382 targeted vehicles (the targeted PSRC vehicles are the vehicles that have a one-year window of trips

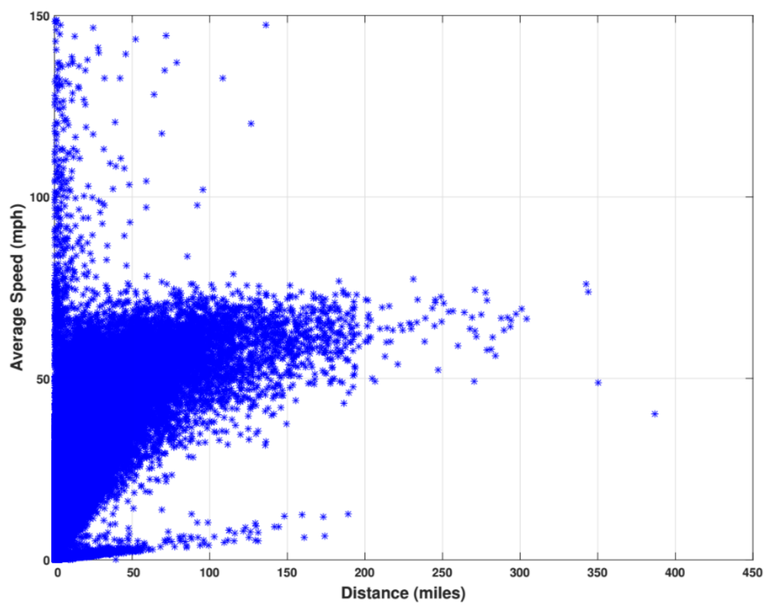


Figure 2.1. Distance-average speed distribution of 653,312 PSRC trips of the 382 vehicles before applying the data correction process.

or more) before the filtration process is applied, while Figures. 2.2 and 2.3 show the distribution of the maximum speeds of the same trips and in Figure 2.4, the distribution of average speeds of the same trips is presented.

In Figure 2.1, the distance of some trips is reasonable, but the average speed is unreasonable. In some cases, the average speeds are greater than 100 mph for short distances while in other cases the average speeds are less than 25 mph for long distances, which indicate erroneous recordings. Similarly, in Figure 2.3, it can be seen that, in some trips, the maximum speed is unreasonable. In all the cases, the maximum speed is greater than 100 mph. Some of these trips are short trips considering their distances. Compared to the average speed of any short trip, its provided maximum speed is apparently incorrect, which indicates that the recordings of these specific cases encountered errors.

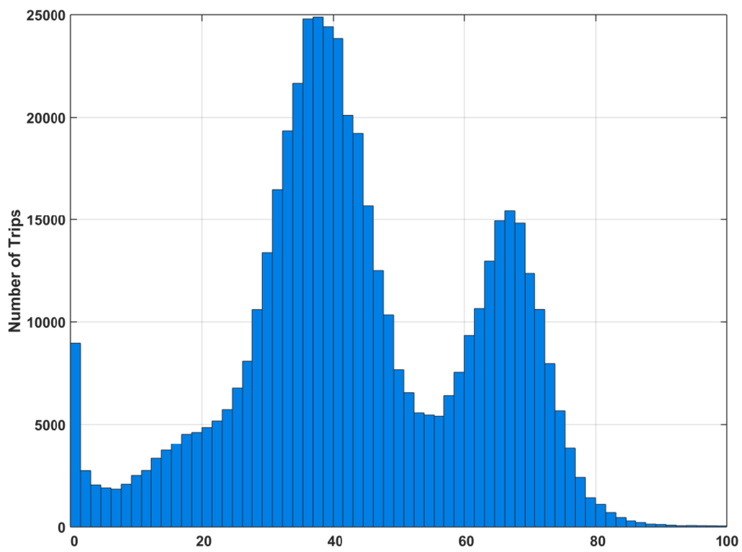


Figure 2.2. Maximum speed distribution of 648,376 uncorrected PSRC trips of the 382 vehicles whose maximum speed was less than or equal to 100 mph.

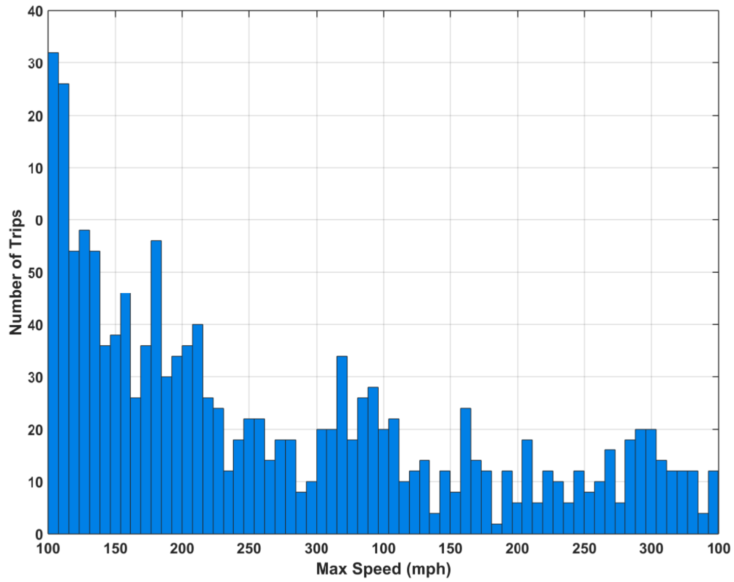


Figure 2.3. Maximum speed distribution of 730 PSRC trips of the 382 vehicles whose maximum speed is between 100 mph and 300 mph. Note that the maximum speed of about 4,206 PSRC trips is greater than 300 mph.

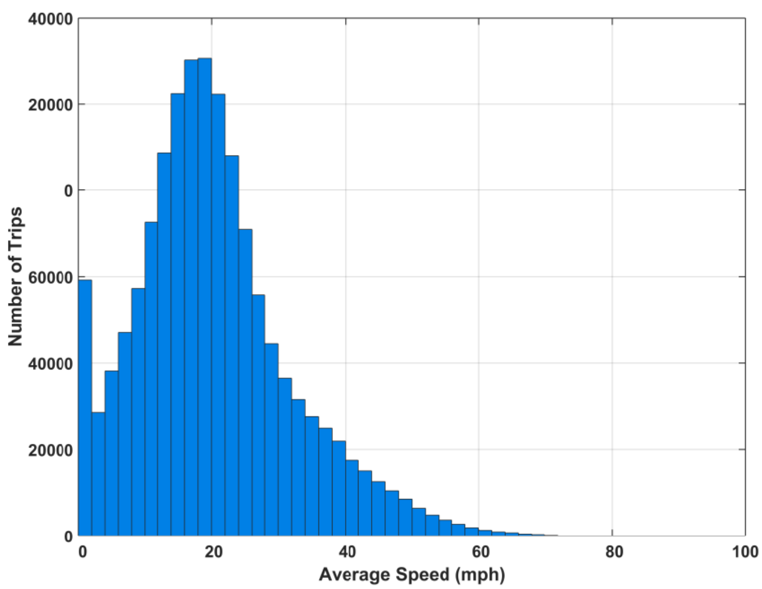


Figure 2.4. Average speed distribution of 653,172 PSRC trips of the 382 vehicles whose average speed is less than 100 mph. Note that the average speed of about 3,217 PSRC trips is greater than 100 mph.

2.2.2 Correction of PSRC Data

Because of the sensitivity of downstream applications to both the quality and integrity of GPS source data, the operating behavior and errors inherently associated with GPS devices has fostered the need for a correction process. The data collected by GPS instruments are prone to errors, such as location drifts and signal drop-outs. Thus, the correction process is required to make the PSRC dataset suitable for the study.

In the correction process, all the trips for each PSRC vehicle are analyzed for any errors or invalid data range. Some of the data errors could be corrected by recalculating some variables or using GPS speed-time data points that are provided by the travel survey source. In some trips, the errors could not be corrected or the trip's data could not be validated due to lack of information. When this is the case, the trip is excluded from further processing. The following four steps are applied to every PSRC vehicle to filter the data and correct errors.

Step 1: Removing Trips with Zero Distance, Zero Duration or Negative Duration: After analyzing PSRC trips, it is noticed that some trips had zero distance and some other trips had zero or negative duration (trip start time and date are the same as trip end time and date or trip end time is before trip start time). These types of trips were specifically marked in the original dataset as "true trips" but they were actually false trips based on my analysis. These trips are removed and are not included in this study.

Step 2: Average Speed Recalculation: The average speed in the original data is calculated using the calculated distance and duration. According to the information provided by the data source [54], the calculated distance is computed from the GPS speed-time data points and might have (large) errors. Therefore, using actual trip distance leads to more accurate average speed calculations. Hence, the average speed of all the PSRC trips is recalculated using the actual distance and duration of the trip:

$$\text{average speed (mph)} = \frac{\text{actual trip distance (miles)}}{\text{trip duration (hours)}} \tag{1.1}$$

Step 3: Maximum Speed Correction: The maximum speeds for several PSRC trips are corrected. As shown in Figures 2.2 and 2.3, in some trips unrealistic maximum speeds were provided. It is clear that the maximum speed calculations encountered errors and these errors can be corrected by referring to the GPS speed-time data points of the vehicle. Based on my investigations, the maximum speed of the trip is the maximum speed value in the GPS speed-time data points (neglecting all unreasonable speed points). The procedure for correcting the maximum speed errors is shown in Figure 2.5.

An upper threshold of 100 mph for the maximum speed is assumed and used to validate every trip including the trips with maximum speed that is less than or equal to 100 mph. The maximum speed for all the PSRC trips are checked and, whenever feasible, correct any trips and, whenever feasible, correct any unmatched (i.e. when reported maximum speed does not equal to the actual maximum speed from GPS speed-time data points) or unrealistic maximum speeds (i.e. when maximum speed is over 100 mph). For every PSRC trip, if the GPS speed-time points are provided and not all of the speed values are greater than 100 mph, the trip maximum speed is calculated as the maximum speed value of the speed points after neglecting all speed points that are more than 100 mph. Then, the trip provided maximum speed is replaced with the new calculated maximum speed if the two maximum speeds do not match. The maximum speed of the PSRC trip is not corrected if the GPS speed-time points are not provided for the PSRC trip or the GPS speed-time points are provided but all of the speed values are greater than 100 mph.

In some PSRC trips, the maximum speed is not provided by the data source. These trips are excluded from the maximum speed correction step because it is noticed that the GPS speed-time data points are also missing in the data source. However, these trips are still used in this study since the trip's maximum speed is not a focus of this study.

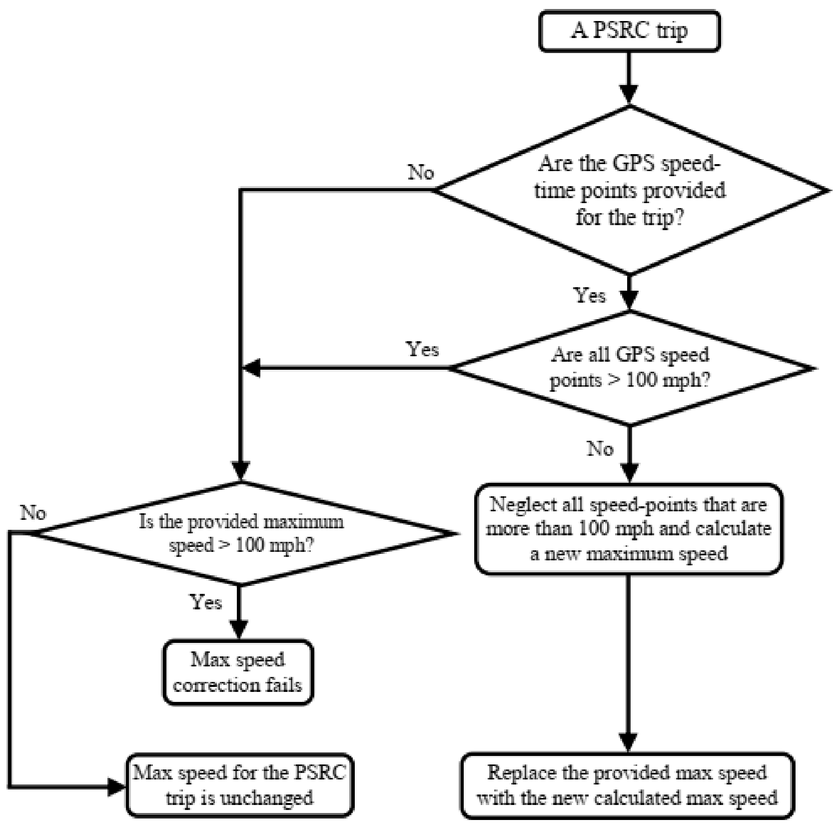


Figure 2.5. The procedure for correcting the maximum speed of the PSRC trip using the GPS speed-time points provided for the PSRC trips.

Step 4: Validation of Distance-Speed Relation of Trips: From Figure 2.1 it can be seen that, for some trips, the relationship between the distance and the average speed may not be correct (e.g., small distance with high average speed). To check for this error and validate the PSRC trips, I subject all the PSRC trips to a simple trip model that I devised for the purpose of validation. To the best of our knowledge, this type of validation is not applied in any of the existing studies in the literature. PSRC trips with actual distance less than or equal to 0.05 miles are excluded from this model test. These trips are considered as “zero distance trips” and are also excluded from the matching process. In the trip-testing model shown in Figure 2.6 that acts as a screener, the acceleration is set to 0.35g and the deceleration to 1g, representing a vehicle achieving 60 mph from 0 mph in 7.82 seconds and a stopping distance of 120 feet when decelerating from 60 mph to a complete stop. According to the real-world testing results provided in an Auto Issue of the Consumer Reports magazine [55], the average time required to accelerate from 0 to 60 mph for 255 of 2018 passenger cars was 7.96 seconds and the average dry-braking distance was 133 feet. Given that the vehicles in the PSRC and ARC surveys were made before 2007 and 2012, respectively, it is reasonable to assume that, as a group, these vehicles’ acceleration and breaking performances are worse than those of the 2018 vehicles. Therefore, using 0.35g for the acceleration and 1g for the deceleration in the testing model is expected to be able to perform effective screening -- excluding those trips that are likely false and keep the trips that are genuine.

By using the provided maximum speed (after recalculation with errors detected and corrected) and the duration of the trip, the trip model as shown in Figure 2.6 is constructed, where d is the trip duration in seconds, υ_{max} is the trip maximum speed in mph, $b = \frac{\upsilon_{max}}{0.35g}$ $(seconds)$, and $c = d - \frac{\upsilon_{max}}{g}$ $(seconds)$. Then the distance and the average speed for the assumed trip model can be calculated from the constructed pattern using the following equations:

$$distance = \frac{(c-b+d)}{7200} \times \upsilon_{max}\ (miles) \tag{1.2}$$

$$average\ speed = \frac{distance}{d} \times 3600\ (mph) \tag{1.3}$$

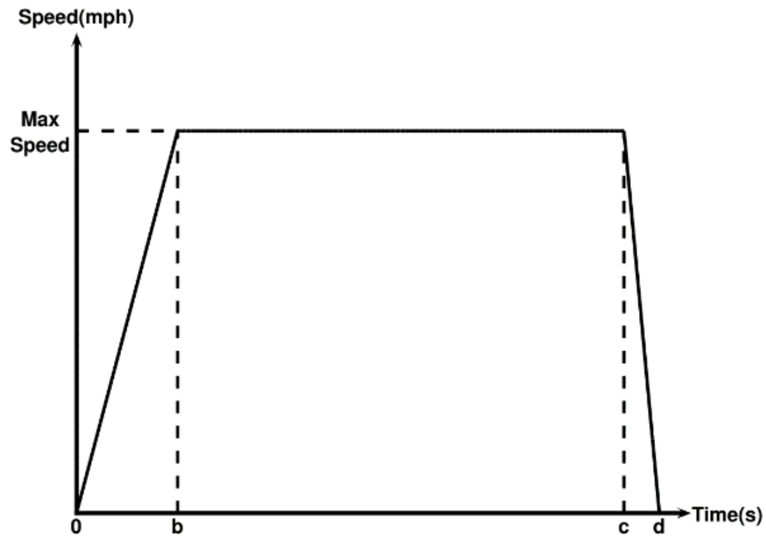


Figure 2.6. Proposed trip model for validating the PSRC trips.

The distance and average speed calculated from the trip model represent a reasonable upper bound on the distance and average speed of an actual trip, given only the duration. If the distance and/or the average speed that is calculated from the constructed pattern is less than the trip provided distance or average speed, then the trip is not counted and is dropped from this study. Also, the trip is dropped from this study if it is not long enough to reach the maximum speed (i.e. c < b in Figure 2.6). Note that in the case of the maximum speed not being provided for a PSRC trip, the trip is excluded from the trip model test, but it is still used in the study because the most important information is the trip distance and average speed. A trip with missing maximum speed but having all the other information can still be useful in many vehicle research studies.

2.2.3 Selection of the Best One-Year Window for Trips

Research such as fuel economy studies should consider all driving circumstances, which implies using the driving data from the trips that took place through the entire year. Thus, I analyze every PSRC vehicle and choose only vehicles that made trips throughout a period of one year or more. For every chosen PSRC vehicle, a one-year sliding window is applied to all the trips made by the vehicle, starting with the first trip and moving on until reaching the last possible one-year, or more, window of trips. This generates multiple consecutive one-year windows of trips. Then, among these one-year windows, the window that has the number of trips closest to the average number of trips of one-year windows of the vehicle is selected as the best one-year window, or the representative window, for the vehicle:

$$average\ number\ of\ trips\ for\ one\ year\ windows = \frac{sum\ of\ number\ of\ trips\ in\ one\ year\ windows}{number\ of\ one\ year\ windows\ for\ the\ vehicle} \quad (1.4)$$

2.2.4 Analysis and Processing of Zero Distance Trips

As mentioned above, the PSRC trips with distance less than or equal to 0.05 miles are considered as "zero distance trips" and they are excluded from the trip model validation step in the data correction process and will also be excluded in the matching procedures. However, these trips are still included in the final generated dataset as short distance trips without velocity profiles. To analyze and explore these trips, I apply the trip model validation test separately against these trips and investigate the percent of these trips that could pass the validation test. Also, these trips are analyzed and investigated based on their destinations and tour categories to explore and study their travel behavior characteristics.

2.3 Processing ARC Dataset

2.3.1 Analysis of ARC Data

The data in the ARC dataset was collected using GPS devices and its quality was deemed reasonable (see Figure 2.7). Specifically, for driving data, the speed data had reasonable ranges, with highest speed being around 100 mph and average speed of around 26 mph. Because the survey was run for a different purpose than our study, the raw data was processed according to the requirements of the survey's objectives. In order to save storage space, the ARC trips have consecutive points at zero speed, also called "idle time", removed from the drive cycle file. Examining the time stamps in the drive cycle is necessary to determine the length of the idle period. The trip average speed data provided by NREL had been calculated based on the GPS speed-time data points for the trip after exclusion of the zero speed points (i.e., idling time) [22, 53]. The actual trip duration was ignored. Driver's trip driving patterns ought to include idle time in addition to actual driving time. Also, in order to simplify processing of the drive cycles by vehicle models, I desire to add the zero speed periods back in the cycle files.

Therefore, I put the idle time explicitly back in all ARC trips. The start and end times and dates are provided for every ARC trip. By using all this information and investigating the GPS speed-time data points for the trip, I add the removed time points at zero speed. To make the ARC trips consistent with the PSRC trips whose average speed was calculated using trip's actual distance and duration, I recalculate the average speed for all the ARC trips based on the actual trip duration (including the idle time) and distance.

Figure 2.7 shows the distance-average speed distribution of the original ARC trips that we obtained after adding the removed time points at zero speed and recalculating the average speed. Compared to the distribution of the PSRC trips shown in Figure 2.1, the distribution of the ARC trips looks more normal where none of the ARC trips had low distance and high average speed, or high distance and low average speed. Figure 2.8 shows the distribution of their maximum speeds which also looks more normal comparing to the distribution of the PSRC trips shown in Figure 2.2.

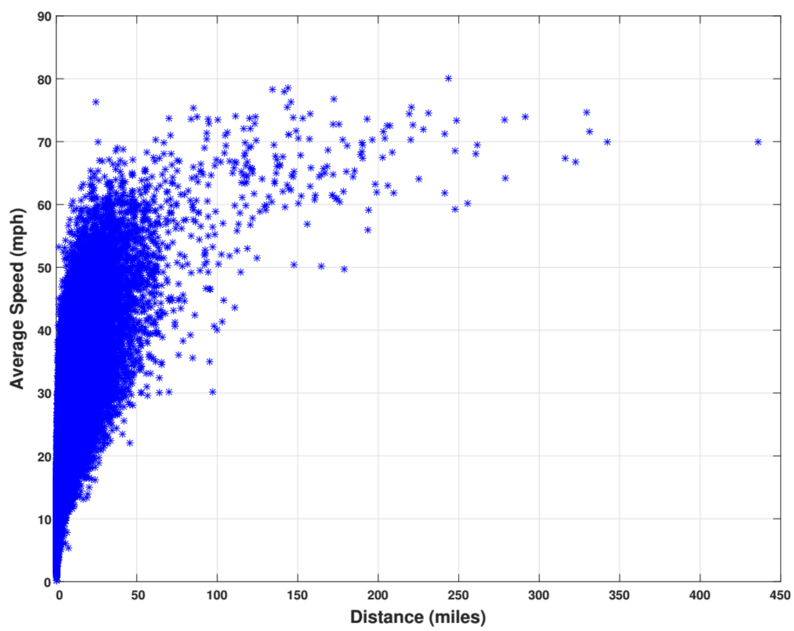


Figure 2.7. Distance-average speed distribution of 39,433 original ARC trips of the 1,651 vehicles after data processing.

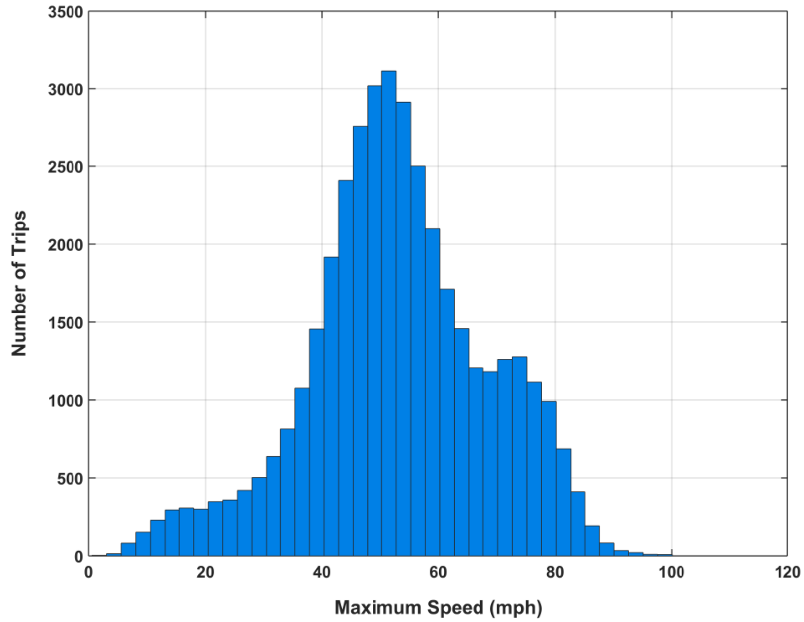


Figure 2.8. Maximum speed distribution of 39,433 original ARC trips of the 1,651 vehicles after data processing.

2.3.2 Generating New ARC Trips from the Original ARC Trips

The main goal of the work in this chapter is to use the PSRC and ARC trips to develop a driver-based second-by-second driving cycle database for vehicle usage patterns covering an entire year. Such a driving cycle database may be produced by using the second-by-second data of the ARC trips and the validated PSRC trip data after applying certain procedures to these trips. This can be accomplished by matching the PSRC trips to the ARC trips based on trip information such as the distance, average speed and duration. For good matching, I require that the two trip datasets involved have very similar distance-average speed distributions. As shown in Figures 2.7 and 2.2, the distributions of the PSRC and ARC trips have some similarity, but some regions of the PSRC distributions are not included in the ARC distributions. To address this problem, and more specifically, to include the PSRC trips that had short duration and high average speed in ARC trips' distributions, new ARC trips are generated from the original ARC trips by considering every driving cycle between each two idle time portions that each of them is greater than or equal to three seconds as a trip (i.e., a micro trip). As a result, we can have trips that have small distances and high average speeds.

2.4 Matching the PSRC Trips by the ARC Original and Micro Trips

After pre-processing the two datasets as described above, the PSRC trips are matched to the trips of the ARC dataset as follows. The trips of every PSRC vehicle are matched to the trips of ARC vehicles based on the key variables of the trip, which are distance, average speed, and a specific duration condition. Generally, the distance of the PSRC trip is first matched by the distances of all the ARC trips with an error band of ± 3%. Then, an average speed error band of ± 3% is applied to the average speeds of the resulting ARC trips. Finally, all ARC trips that passed the previous two matching steps are subject to a duration test shown in Eq. 1.7 - the duration of the ARC trip should not be greater than the duration of the PSRC trip plus the soak time. Vehicle soak time is the time duration a vehicle's engine is off. The soak time for a PSRC trip is the time length between the end of a trip and the start of the next trip. If more than one ARC trip meets these criteria, then one of them is randomly chosen as the final ARC trip that matched the PSRC trip and the others are saved as diverse representatives of the same PSRV trip. Figure 2.9 shows the main procedure for matching the PSRC trips by single original ARC trips using the above-mentioned strategy.

If the matching procedure shown in Figure 2.9 could not result in any original ARC trip, different matching strategies are then applied. First, the PSRC trip is matched by combining up to four original ARC trips using the procedure shown in Figure 2.10. In this procedure, the average speed of the PSRC trip is first matched by the average speeds of all the original ARC trips with an error band of ± 3%. Then, among the resultant original ARC trips whose distances are less than the distance of the PSRC trip, the trip with the closest distance to the PSRC trip's distance is selected. Finally, the selected

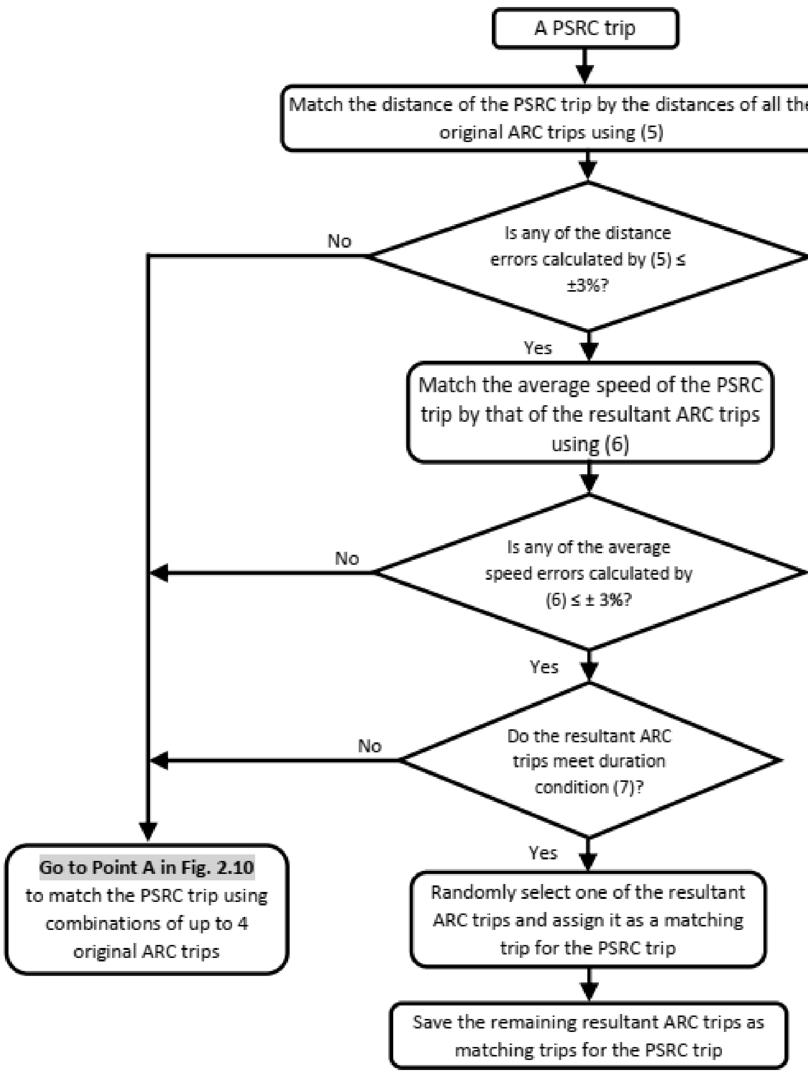


Figure 2.9. The procedure for matching the PSRC trip by single original ARC trips.

original ARC trip is combined with up to 4 trips of the resultant original ARC trips to achieve the satisfaction of error band of ± 3% for the distance and average speed and the satisfaction of the duration condition for the combined trip. If the combination procedure failed to generate a matching trip for the PSRC trip, the PSRC trip is matched by single ARC micro-trips as shown in Figure 2.11 following the same strategy as in Figure 2.9 by replacing the original ARC trips with the ARC micro-trips.

$$\text{distance error } (\%) = \frac{\text{distance of current PSRC trip} - \text{distances of all ARC trips}}{\text{distance of current PSRC trip}} \times 100 \qquad (1.5)$$

$$average\ speed\ error\ (\%) = \frac{PSRC\ trip's\ average\ speed - average\ speed\ of\ matched\ ARC\ trips}{PSRC\ trip's\ average\ speed} \times 100 \qquad (1.6)$$

$$ARC\ trip's\ duration \quad \leq PSRC\ trip's\ duration\ +\ PSRC\ trip's\ soak\ time \qquad (1.7)$$

If the PSRC trip still could not be matched by an ARC trip(s), the ARC combination procedure shown in Figure 2.10 is repeated, but using both original and/or ARC micro-trips with as many combinations as needed preferring the original ARC trips. By combining ARC trips (original and/or micro trips) as shown in Figure 2.10, the distance of the generated ARC trip can be increased while maintaining the average speed. Finally, in the case when all the previous procedures failed to find a matching ARC trip for the PSRC trip, a procedure that modifies an original ARC trip to match the PSRC trip is applied as shown in Figure 12. In this procedure, the distance of the PSRC trip is first matched by that of all the original ARC trips with an error band of ± 3%. Then, among the resultant ARC trips, the trip whose average speed is greater than the average speed of the PSRC trip by the least amount is selected. Then, the idle time that is required to reduce the average speed of the selected ARC trip to make it within an error band of ± 3% of the average speed of the PSRC trip is added to this ARC trip provided that the added idle time is less than one-third of the PSRC trip's duration. Finally, if the resultant ARC trip satisfies the duration condition presented in (7), a new vehicle ID and trip ID are generated for the resultant ARC trip and this trip is assigned as the matching trip for the PSRC trip. By using this procedure, the length of the idle periods of the trip can be increased to reduce the average speed of the trip without changing its distance. In the case when all the four procedures failed to find a matching ARC trip for a PSRC trip, that specific PSRC trip is excluded from this study. The matching procedures produced a dataset that inherits the usage patterns of the PSRC dataset (the long time-period covering the entire year) and the advantages of the ARC dataset (the high time resolution of the clean GPS speed-time data points).

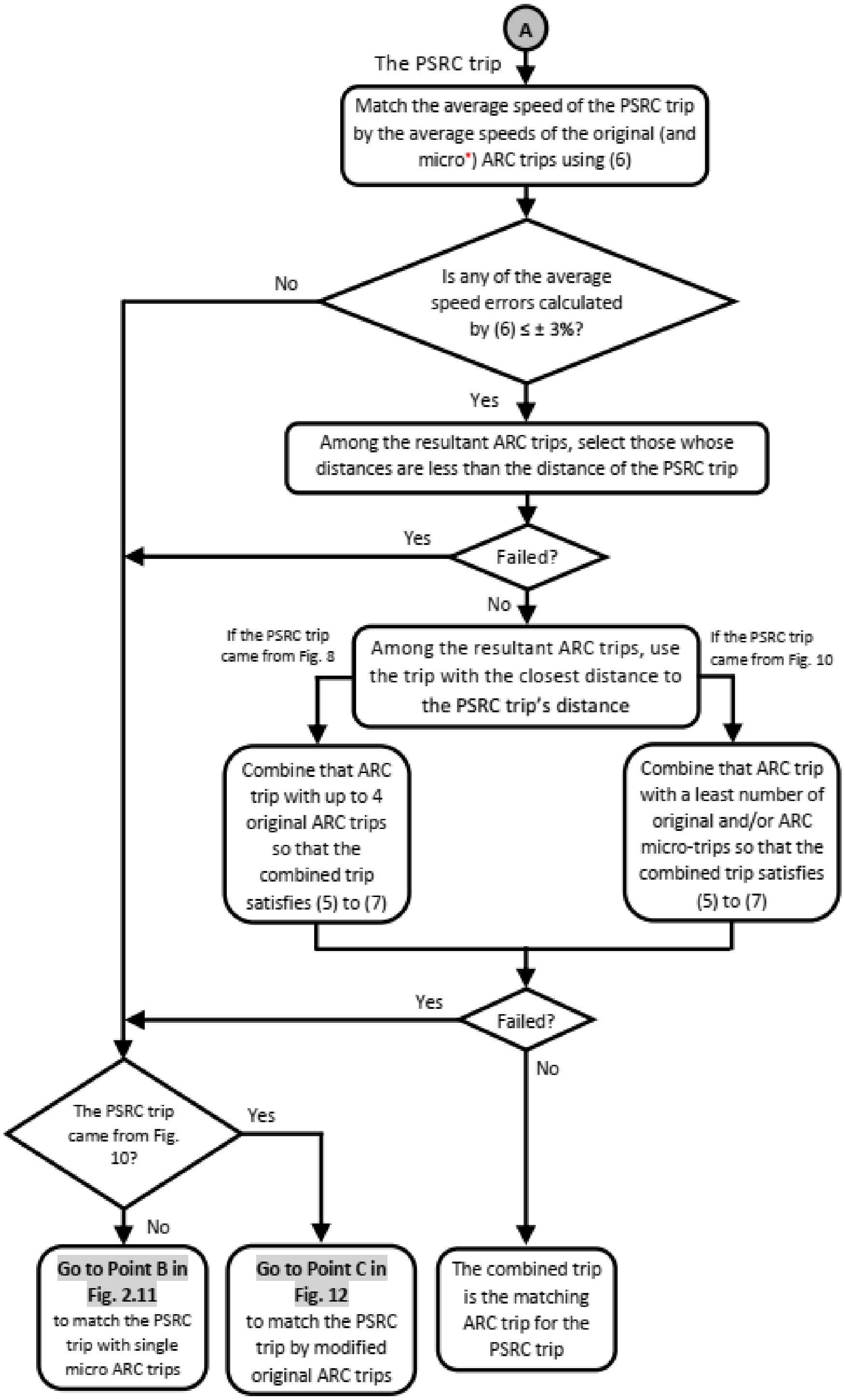


Figure 2.10. The procedure for matching the PSRC trip by a combination of ARC trips. *If the procedure is called from Figure 2.10, both original and ARC micro-trips may be used with as many original trips to be utilized as possible.

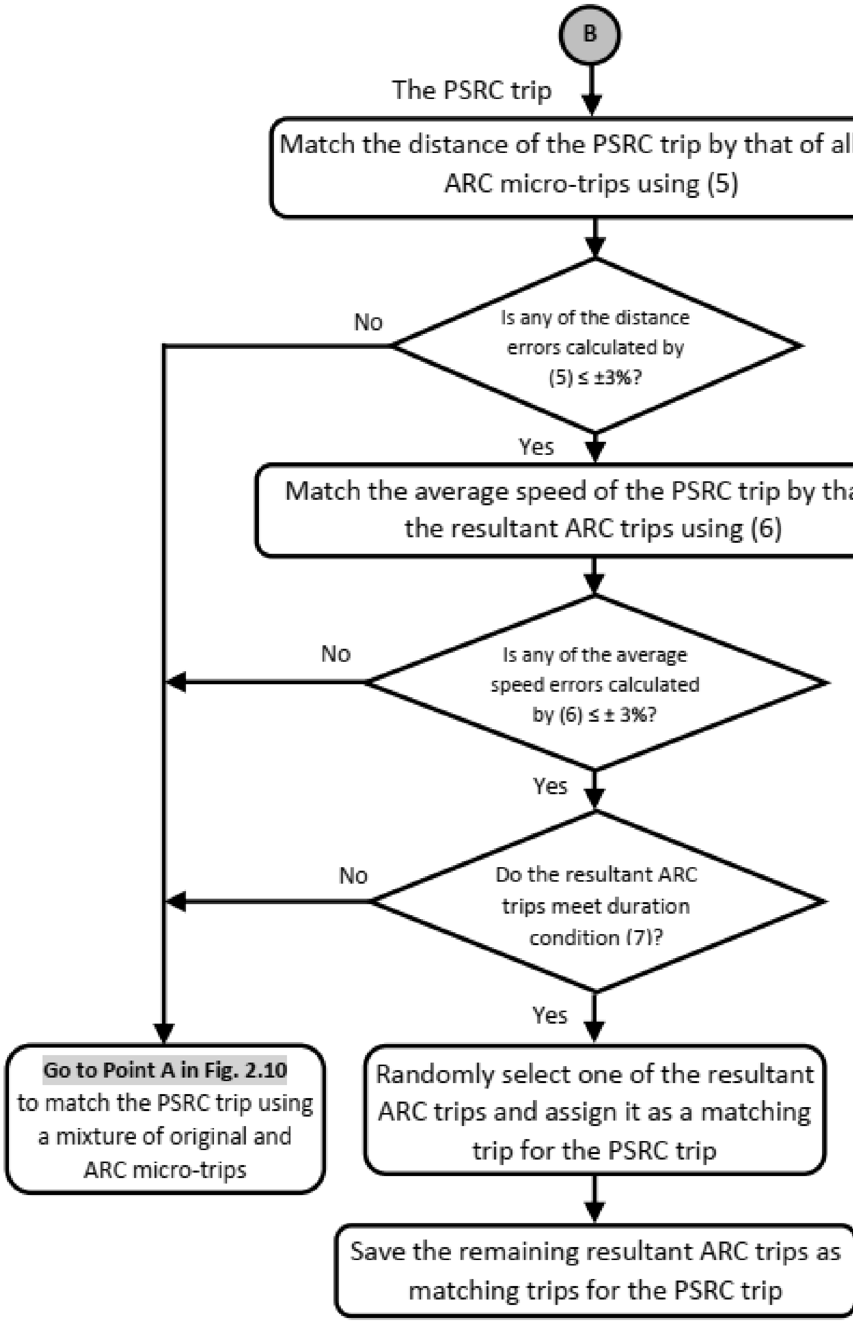


Figure 2.11. The procedure for matching the PSRC trip by single ARC micro-trips.

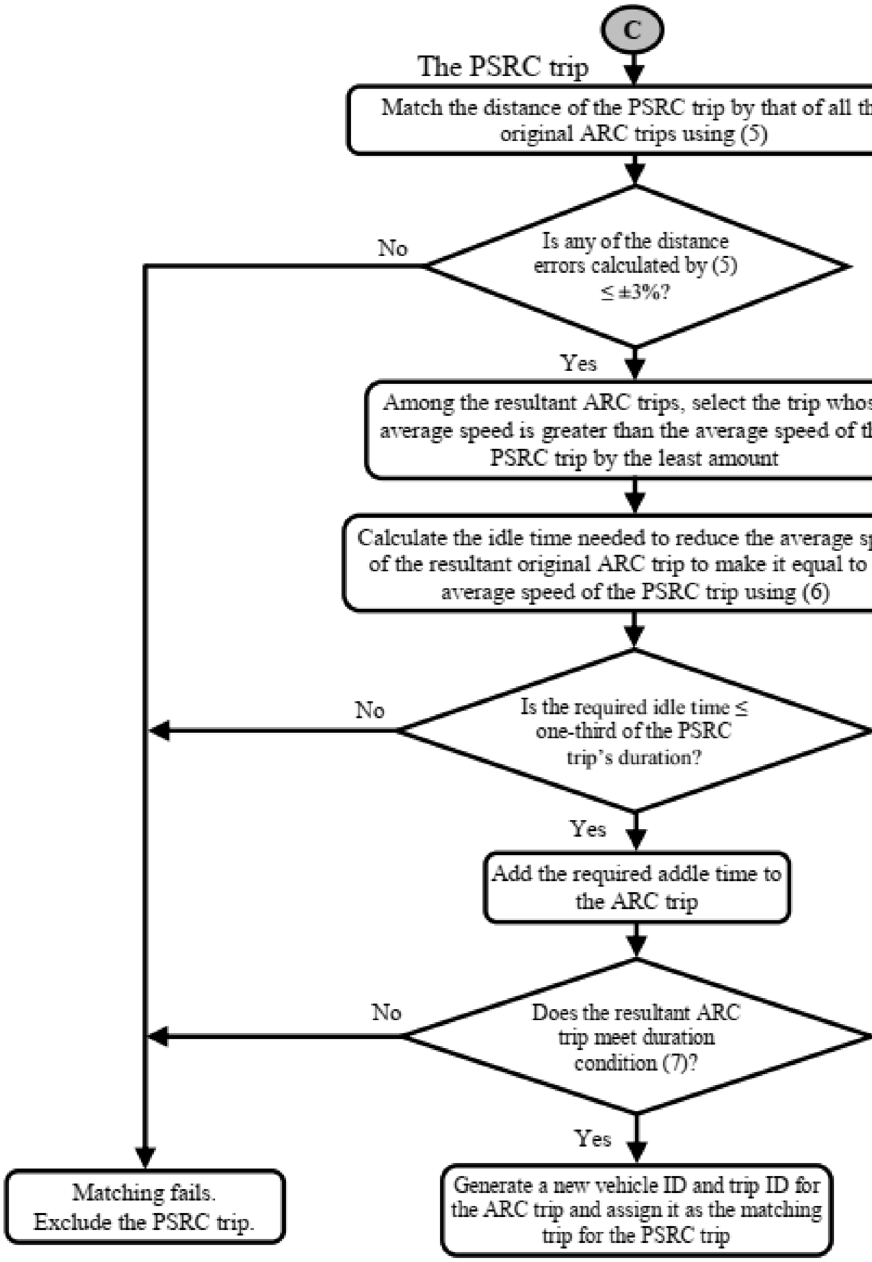


Figure 2.12. The procedure for matching the PSRC trip by a single modified original ARC trip.

CHAPTER 3

NEW SECOND-BY-SECOND TRIP DATASET GENERATED FROM THE PSRC AND ARC DATASETS

3.1 Results of Processing PSRC Dataset

The results of filtering and processing the PSRC trips are shown in Table 3.1. It can be observed that after the correction process, the trips have a reasonable distribution. From Table 3.1, 3.43% of the PSRC trips had either a maximum speed over 100 mph or an erroneous maximum speed. Most of these trips were correctable and were fixed. Only 0.15% of the trips could not be corrected because of the limitations of the GPS speed-time data points.

Table 3.1. Results of the filtration process of PSRC trips.

	Mean (%)	**STD (%)**
Trips with zero actual duration	5.86	5.62
Trips with zero actual distance	5.76	5.64
Trips failing the trip model test	5.30	2.75
Trips with incorrect maximum speeds	3.43	1.06
Trips with corrected maximum speeds	3.37	0.99
Trips removed due to erroneous maximum speeds	0.06	0.15
Trips with negative duration	0.0001	0.0001

Figure 3.1 shows the distance-average speed distribution of the corrected PSRC trips of the 382 vehicles that passed the one-year window process (we call them the targeted vehicles) excluding "zero distance trips". Compared with Figure 2.1, the distribution was improved and the new distribution was similar to the distribution of the ARC trips. The

trips with a long distance and an unreasonably low average speed were corrected, so were the trips with a short distance and an unreasonably high average speed. Figure 3.2 provides a closeup examination of the distance-average speed distribution of the PSRC trips shown in Figure 2.1. The theoretical upper limit boundary imposed by the trip model (Figure 2.6) was also exhibited. All the corrected PSRC trips passed the model because they were all within the boundary. Figure 3.3 shows that the maximum speeds of the PSRC trips of the targeted vehicles tend to follow a bi-modal distribution, with a large number of trips with low maximum speed. Figure 3.4 shows the improvement in the average speed of the PSRC trips.

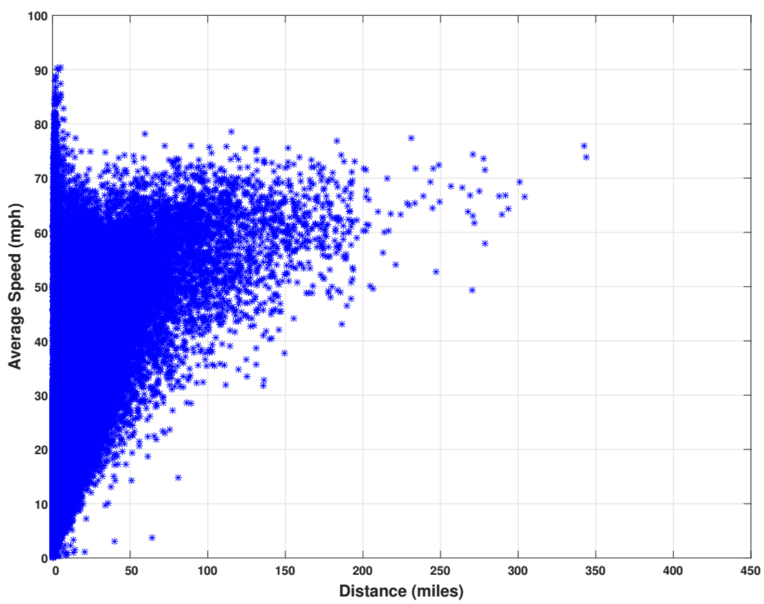


Figure 3.1. Distance-average speed distribution of 508,559 PSRC trips (excluding zero_distance_trips) made by the 382 vehicles that fitted the one-year window after the data correction process.

The results of applying the best one-year window process are shown in Figures 3.5 and 3.6. Figure 3.5 illustrates the distribution of the number of one-year windows of the 382 targeted PSRC vehicles after the filtering process. The mean of the number of the one-year windows was 58 windows. Figure 3.6 shows the distribution of the number of the trips in the best one-year windows of the targeted vehicles after the filtering. The average number of the trips in the best one-year window was 1,396 trips while the minimum number of the trips in a best one-year window was 294 trips.

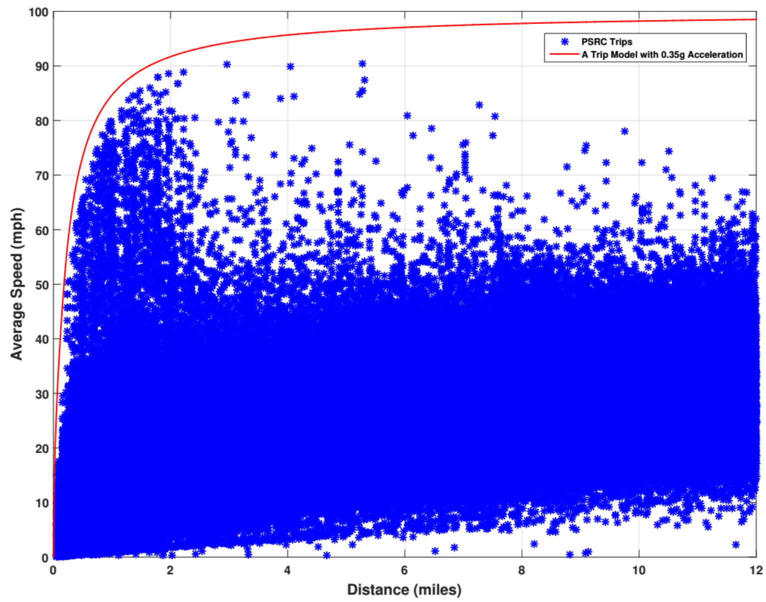


Figure 3.2. A closeup view of the distance-average speed distribution of the PSRC trips shown in Figure 3.1.

Figure 3.7 presents the distribution of the number of driving days in the best one-year window for the targeted PSRC vehicles. We noticed that most of the targeted vehicles had more than 200 driving days in their best one-year windows. The average of the driving days in the best one-year windows was 283 days, which means the average driver in the PSRC data set used their vehicles for 77.5% of the days in the year.

Some drivers in the PSRC dataset used their vehicles nearly every day, but the most typical usage pattern is around 300 days per year as Figure 3.7 shows. There was also a large variation in the number of trips taken per year, from as little as 250 trips to nearly

3000 trips per year as described in Figure 3.6. From Figure 3.8, it can be seen that there is a strong correlation between the number of yearly trips and the number of days per year that a vehicle is used.

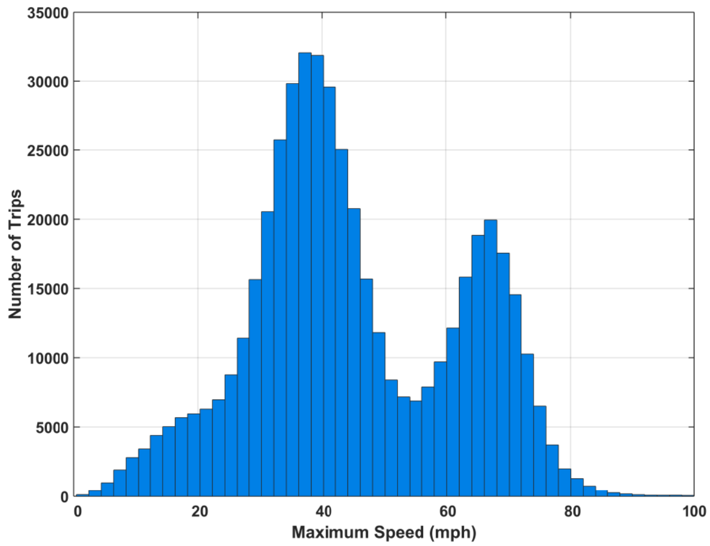


Figure 3.3. Maximum speed distribution of 508,559 corrected PSRC trips (excluding zero_distance_trips) made by the 382 vehicles that fitted the best one-year window after the data correction process.

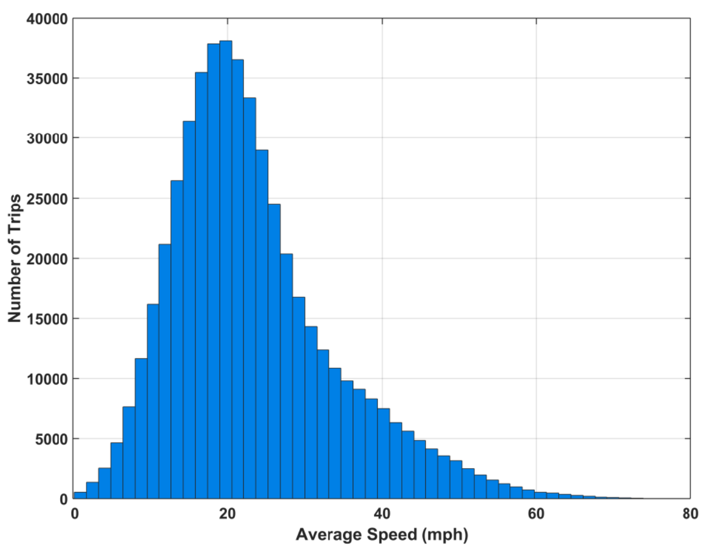


Figure 3.4. Average speed distribution of 508,559 corrected PSRC trips (excluding zero_distance_trips) made by the 382 vehicles that fitted the best one-year window after the data correction process.

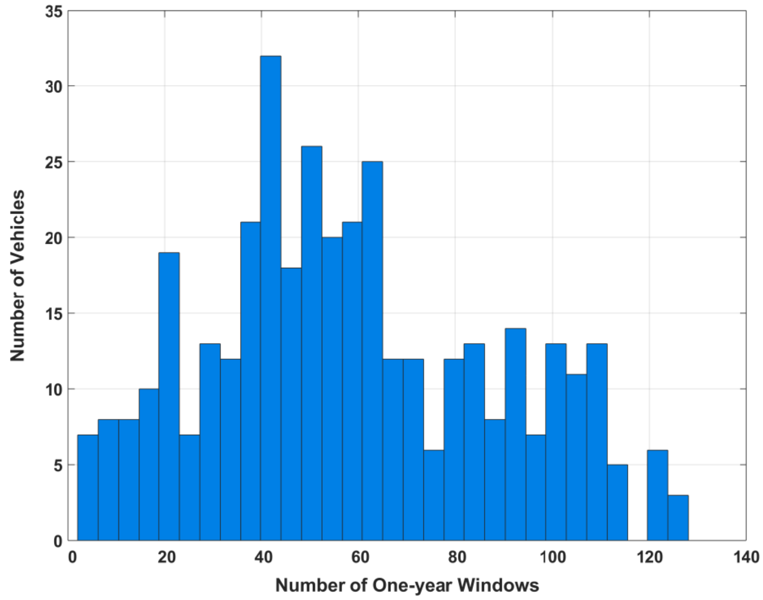


Figure 3.5. Distribution of the number of one-year windows for the 382 PSRC vehicles after the data correction process.

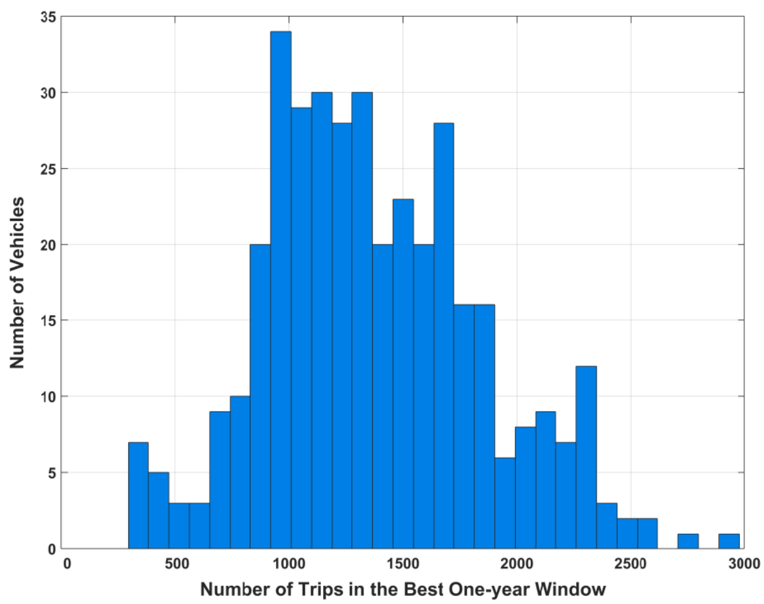


Figure 3.6. Distribution of the number of trips in the best one-year windows for the 382 PSRC vehicles after the data correction process.

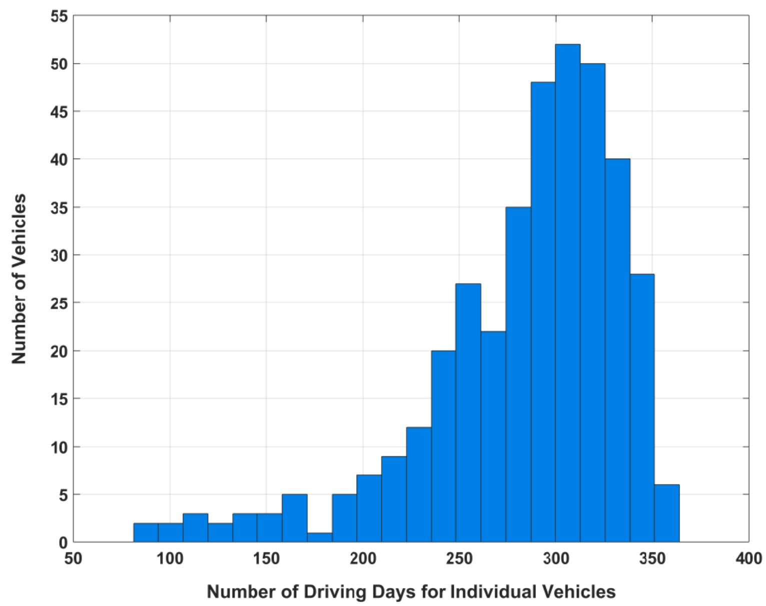


Figure 3.7. Distribution of the number of driving days in the best one-year windows for the 382 PSRC vehicles after the data correction and pre-processing steps.

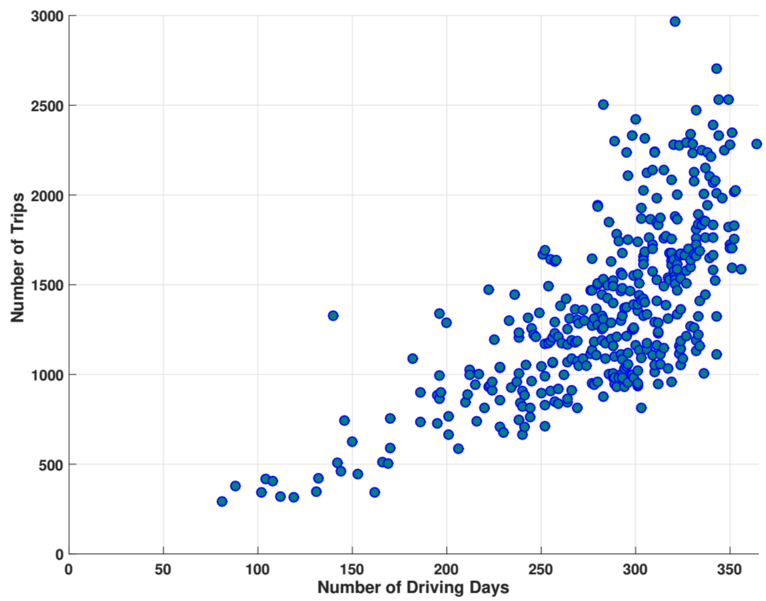


Figure 3.8. Correlation between the number of driving days and the number of trips in the best one-year windows for the 382 PSRC vehicles after the data correction process.

Figures 3.9 – 3.11 show the results of analyzing and processing the PSRC zero distance trips (trips with distance less than or equal to 0.05 miles). Out of the total number of trips for the entire dataset, there were 15,657 trips (3%) that were considered as zero distance trips and (in contrast, the percent of zero distance trips in the ARC dataset is only 0.4%). After processing these trips, it was found that the majority of these trips (75% as shown in Figure 3.9) were trips among home-to-home tours. Figure 3.9 shows the distribution of percent of zero distance trips made by the 382 PSRC vehicles based on the four tour categories provided by the original PSRC travel survey.

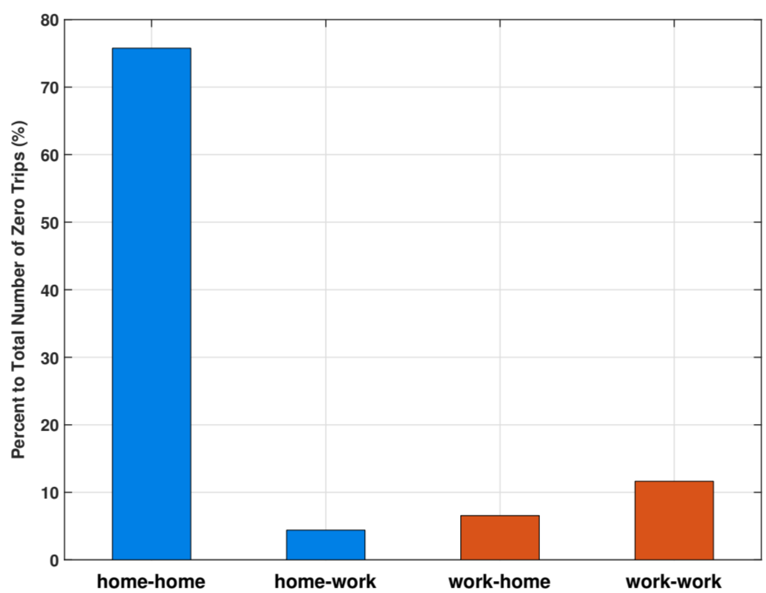


Figure 3.9. Distribution of percent of the four tour categories in the total zero distance trips (15,657 trips) made by the 382 PSRC vehicles.

As mentioned in Chapter 2, for the analysis purpose, all zero distance trips were tested separately against the trip model validation test discussed in Chapter 2 and it was found that only 2,968 trips passed this test, which is about 19% of the total number of zero distance trips, despite the fact that 99% of these trips were marked as good trips by the original PSRC travel survey. Compared to the ARC dataset, all zero distance trips in the ARC dataset passed the trip validation model. The distribution of the percent of each category of the four tour categories in the zero distance trips that passed the trip model test is shown in Figure 3.10 and it is very similar to the distribution in all zero distance trips shown in Figure 3.9. From Figure 3.11 it can be noticed that 48% of these zero distance trips were either from-home or to-home trips while the percent of from-work and to-work trips was 14%. The percent of trips with other destinations was 38%. Based on the original PSRC travel survey [52], a recorded trip is the vehicle activities (driving and idling activities) that take place from the event of turning the key on to the event of turning the

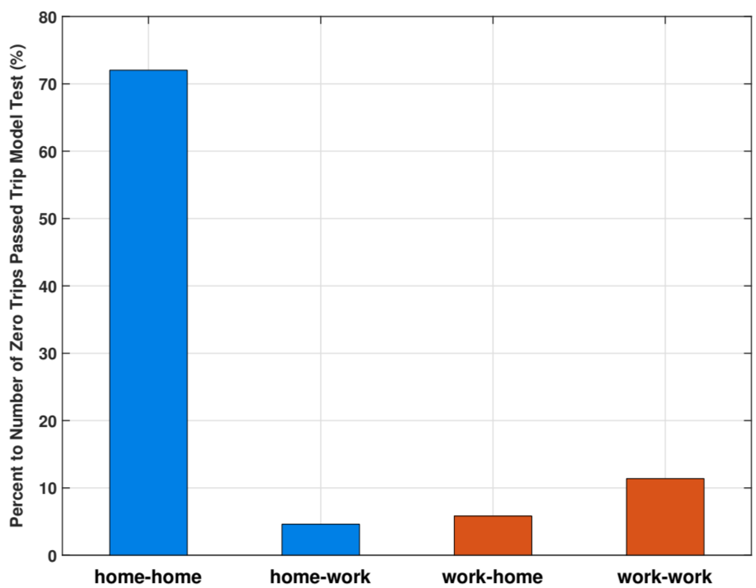


Figure 3.10. Distribution of percent of the four tour categories in the 2,968 zero distance trips made by the 382 PSRC vehicles and passed trip validation model.

key off. Hence, 48% of the zero distance trips that passed the trip model test, were real short trips either from-home where the driver leaves home and stops at a close location, with turning the key off, for a certain purpose, for example visiting a neighbor, or to-home where the driver stops before reaching home, but close to home for a certain purpose with turning the key off and then start the zero distance trip towards home. 38.6% of these to-home or from-home trips were actually trips made from home and to home at the same time. This means that these trips are actually short-distance home-home tours with just one trip made in such a way that a driver heads from home to a close location with distance less than or equal to 0.05 miles for a specific purpose such as checking the mail box without turning the key off and then coming back home. 38% of the total zero distance trips that passed the trip validation model were short trips between any two locations that are 0.05 miles far from each other or less. An example of these trips is moving a vehicle from one slot to another in a parking lot.

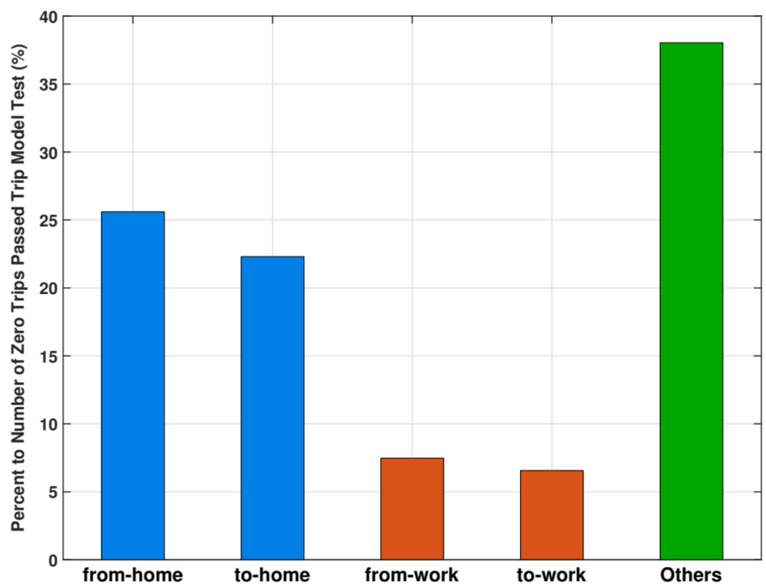
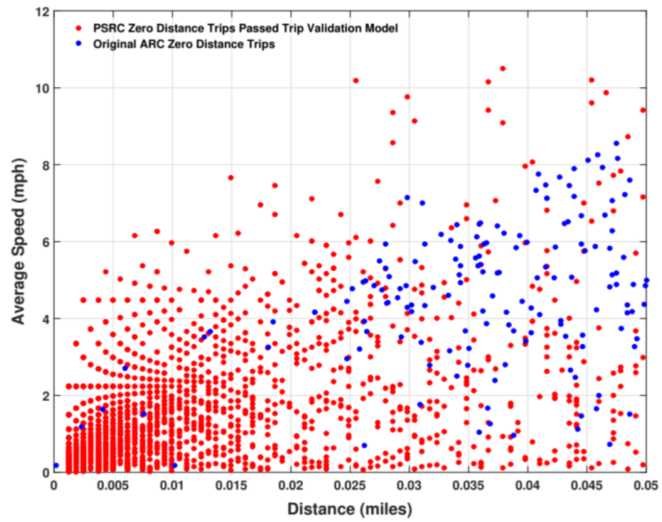
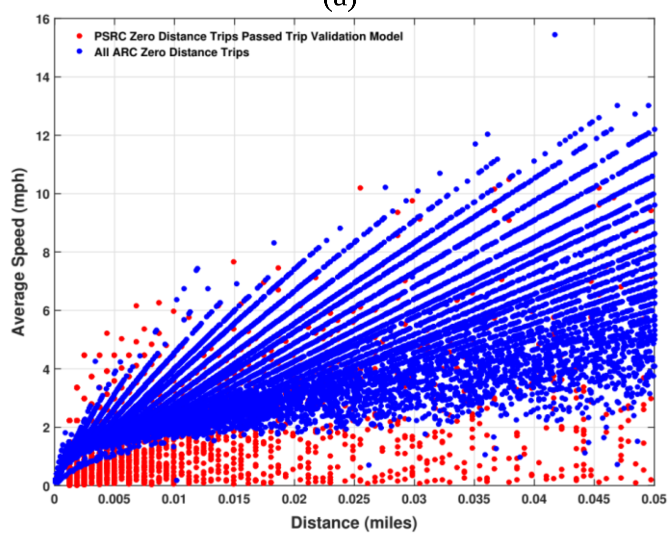


Figure 3.11. Distribution of percent of trip destinations in the zero distance trips made by the 382 vehicles and passed trip validation model.

Figure 3.12 demonstrates the distance-average speed distribution of the 2,968 zero distance trips made by the 382 PSRC vehicles and passed the trip validation model and the zero distance trips of the ARC trips. Figure 3.12(a) shows the distance-average speed distribution of the 2,968 zero distance trips made by the 382 PSRC vehicles and passed



(a)



(b)

Figure 3.12. a) Distance-average speed distribution of the 2,968 zero distance trips made by the 382 PSRC vehicles and passed the trip validation model and the 153 zero distance trips of the original ARC trips. b) Distance-average speed distribution of the same 2,968 PSRC zero distance trips and the 17,705 zero distance trips of the original ARC and sub-trips.

the trip validation model compared to the distance-average speed distribution of the 153 zero distance trips of the original ARC trips and Figure 3.12(b) shows the distance-average speed distribution of the same PSRC trips compared to the distance-average speed distribution of the 17,507 zero distance trips of the original and ARC sub-trips. From Figure 3.12, it can be noticed that most of the PSRC zero distance trips that passed the trip validation model has low average speed and compared to the ARC zero distance trips we may infer that some of these trips encountered more idling time (i.e. they are trips with short distance and long duration) and some of them may be just very short local trips where the driver turns the key on and the vehicle moves in low speed to a close location then the key is turned off. Also, the results shown in Figure 3.12 indicates that only few of the mentioned PSRC zero distance trips can be matched by the original ARC zero distance trips and several of several of them may not be matched either by the zero distance trips of the original or the ARC sub trips.

3.2 Results of Processing ARC Dataset

From Figures 3.13 and 3.14, it can be seen that the ARC micro-trips increased the regions of the distance-average speed distribution of the ARC trips and improved the ability of the ARC trips to match the PSRC trips. 143,905 trips were created from the 39,433 original ARC trips.

As shown in Figure 3.15, the overlap region of the distance-average speed distributions of the PSRC trips and the ARC trips increased because of the inclusion of the ARC micro-trips, especially in the low distance region. As will be seen in the next section, the ARC micro-trips contributed to about 1% of the matching results. In other words, 1% of the PSRC trips failing to be matched by the original ARC trips and were matched by the

ARC micro-trips. The generation of ARC micro-trips increases the number of ARC trips that have short distances.

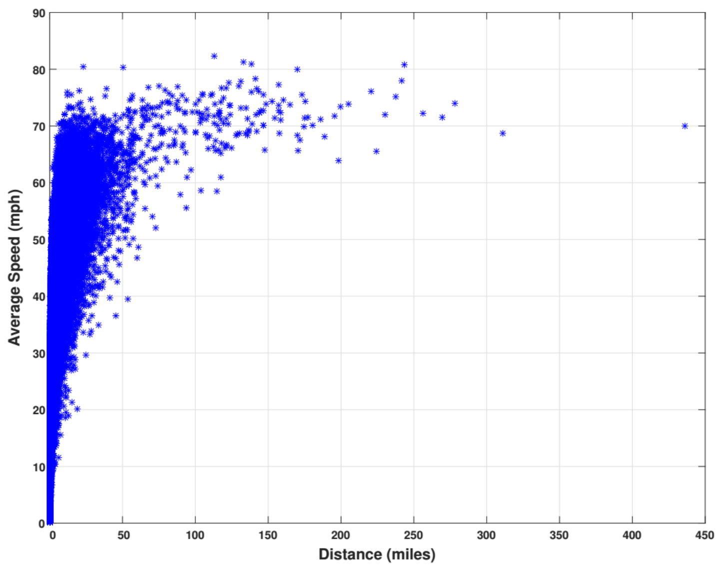


Figure 3.13. Distance-average speed distribution of 143,905 ARC micro-trips.

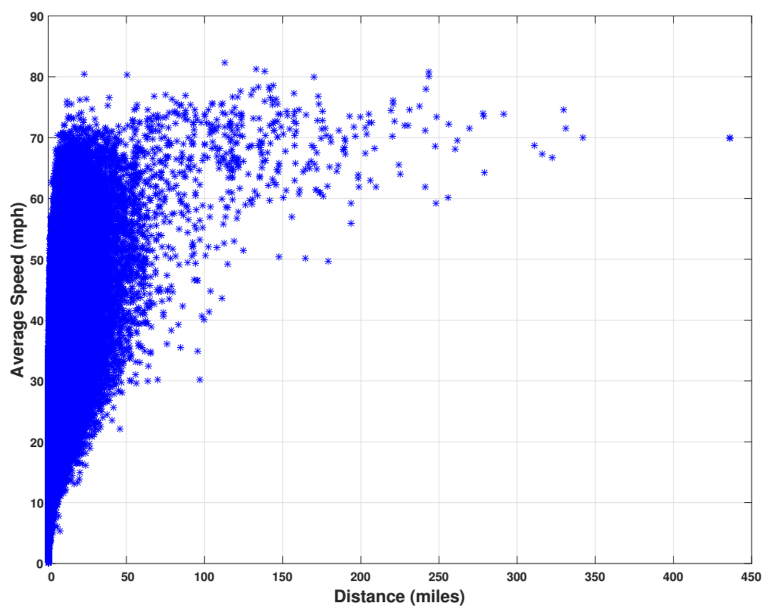


Figure 3.14. Distance-average speed distribution of 183,338 ARC trips composed of both the original and ARC micro-trips.

As shown in Figure 3.15, the overlap region of the distance-average speed distributions of the PSRC trips and the ARC trips increased because of the inclusion of the ARC micro-trips. As will be seen in the next section, the ARC micro-trips contributed to about 1% of the matching results. In other words, 1% of the PSRC trips failing to be matched by the original ARC trips and were matched by the ARC micro-trips.

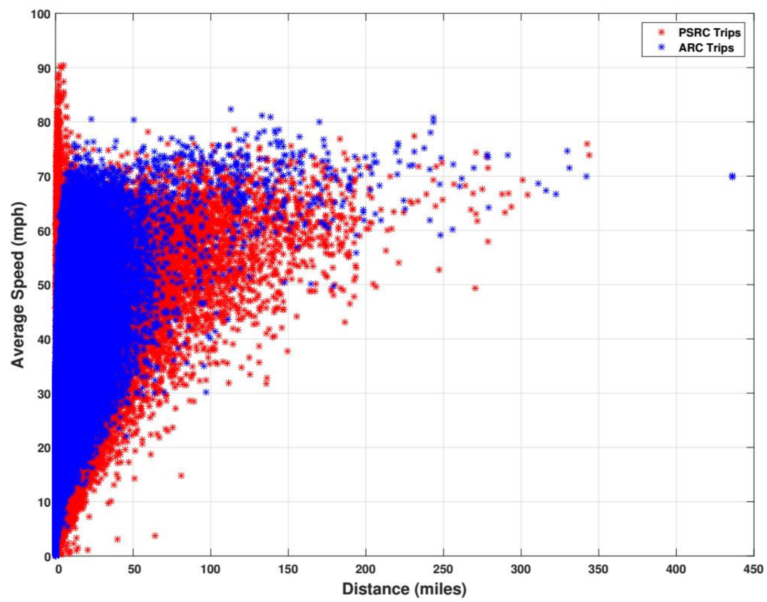


Figure 3.15. Distance-average speed distribution of 183,338 ARC trips composed of both the original and ARC micro-trips and 524,197 PSRC trips made by the 382 vehicles fitting the one-year window after the data correction process.

3.3 Results of Matching the PSRC Trips by the ARC Trips

The fraction of PSRC trips matched by the ARC trips was very high. Figure 3.16 shows that 99.978% of the targeted PSRC trips were successfully matched by the ARC trips. Only 0.278% of the PSRC trips could not be matched by the ARC trips because of average speed mismatch and only 0.0311% of the PSRC trips failed to meet the duration condition. None of the targeted PSRC trips failed to be matched by the ARC trips due to distance mismatch.

Table 3.2 shows the details of the successful matching results. Note that 97.47% of the matched trips were achieved by using only one original ARC trip (i.e., no combination of ARC trips was needed) while 1% of the matched trips were obtained by using only one ARC micro-trip.

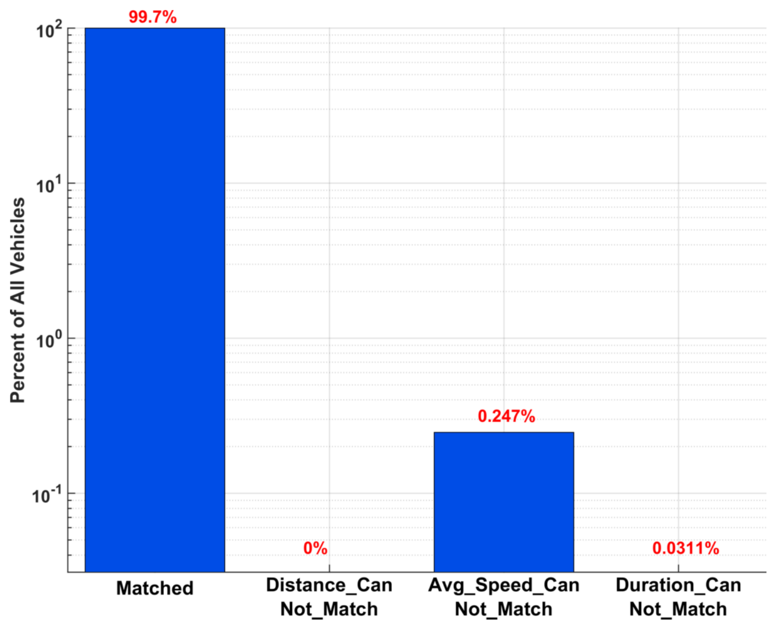


Figure 3.16. Results of matching the 508,559 PSRC trips by the ARC trips subject to a distance error band of ±3% and an average speed error band of ±3%.

Table 3.2. Results of the matching all PSRC trips by ARC trips.

	(%)
One of the original ARC trips	97.470
One of the ARC micro-trips	1.000
Combination of two original ARC trips	1.160
Combination of three original ARC trips	0.100
Combination of four original ARC trips	0.041
Combination of more than four original ARC trips	0.220
Modified ARC trips	0.009

There were 1.301% and 0.22% of the matched trips that were respectively produced by combining four or less and more than four of the original and ARC micro-trips. Only 0.009% of the PSRC matched trips were attained by modifying the original ARC trips by adding or removing their idle times. Overall, 99.978% of the dataset total number of trips were successfully matched and the resultant dataset has a total 508,447 of trips.

Figure 3.17 shows the distribution of the matching percentage of the targeted PSRC vehicles, which was satisfactory. Each and every trip of around 30% of the 382 targeted vehicles (114 vehicles, to be exact) was completely matched. The mean of the matching percentage for the 382 PSRC targeted vehicles was 99.72% and the minimum matching percentage was 95.25%.

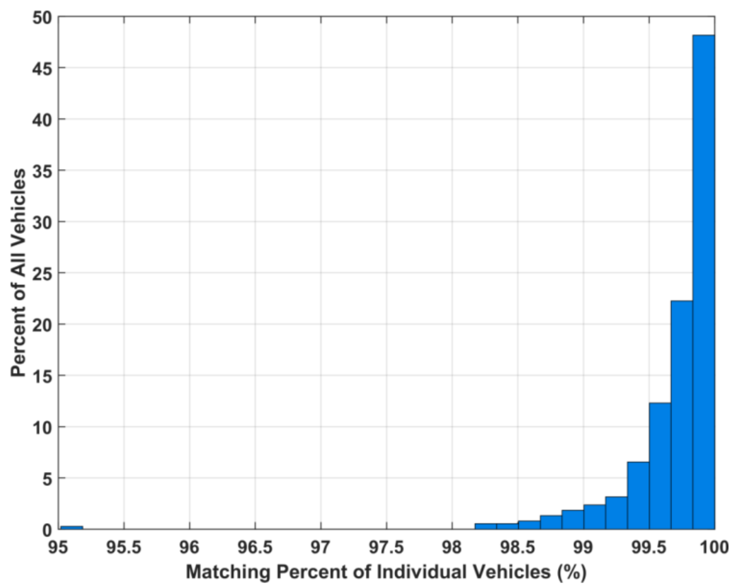


Figure 3.17. Matching percentage distribution of the 382 PSRC vehicles subject to a distance error band of ±3% and an average speed error band of ±3%.

In Figure 3.18, the distribution of the distance differences and the distance errors of the targeted PSRC trips are presented. An ideal matching process should not result in a matched ARC trip whose distance is substantially different from the distance of the PSRC trip being matched. Hence, we restricted the matching distance error to be ±3%. We calculated the percent of the total yearly distance error between the targeted PSRC trips and the matched ARC trips. We found that that percent was a mere 0.0557%. The yearly percent distance errors were randomly distributed around a mean of 0.03%, which is near zero. This indicates that overall the change in the total yearly distance was very small for the matching trips.

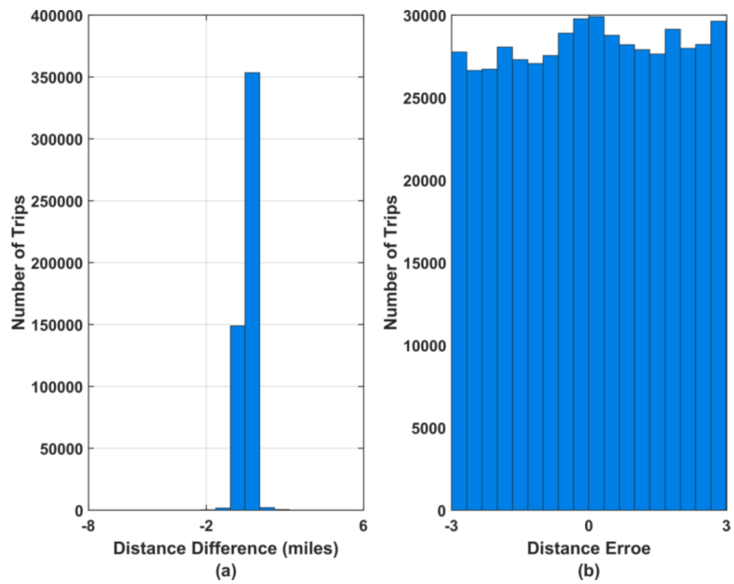


Figure 3.18. a) Distribution of distance differences of the PSRC trips after matched by the ARC trips. b) Distribution of distance errors for the same PSRC trips after they were matched by the ARC trips.

From Figures 3.19 and 3.20, the overall results indicate that the matching distance error and the average speed error were approximately normally distributed. The mean of the distance errors was 1.48% whereas for the average speed errors the mean was 1.49%. Notice that the standard deviations of these two errors were quite low - 1.72% for the matching distance error and 1.73% for the matching average speed error, confirming the distributions to be close to uniform.

Also, by looking at the data histograms, it can be seen that neither of these distributions is normal. Rather than attempting to fit statistical distributions to these datasets, my method uses the actual data itself to empirically describe driver usage patterns.

Figure 3.21 shows some examples of the driving cycles of some PSRC trips after being matched by different ARC trips using the different matching procedures. Figure 3. 21(a), shows the driving cycle of a PSRC trip with 2.01 miles distance, 22.27 mph average speed, and 325 seconds duration that is matched by an original ARC trip. Figure 3.21(b) shows the driving cycle of a PSRC trip with 0.98 miles distance, 2.08 mph average speed, and 1,698 seconds duration matched by combining four original ARC trips. Figure 3.21(c) shows the driving cycle of a PSRC trip with 0.28 miles distance, 19.33 mph average speed, and 53 seconds duration, which is matched by an ARC micro-trip. Finally, Figure 3.21(d) shows the driving cycle of a PSRC trip with 0.25 miles distance, 2.27 mph average speed, and 1,310 seconds duration that is matched by combining more than four original ARC trips.

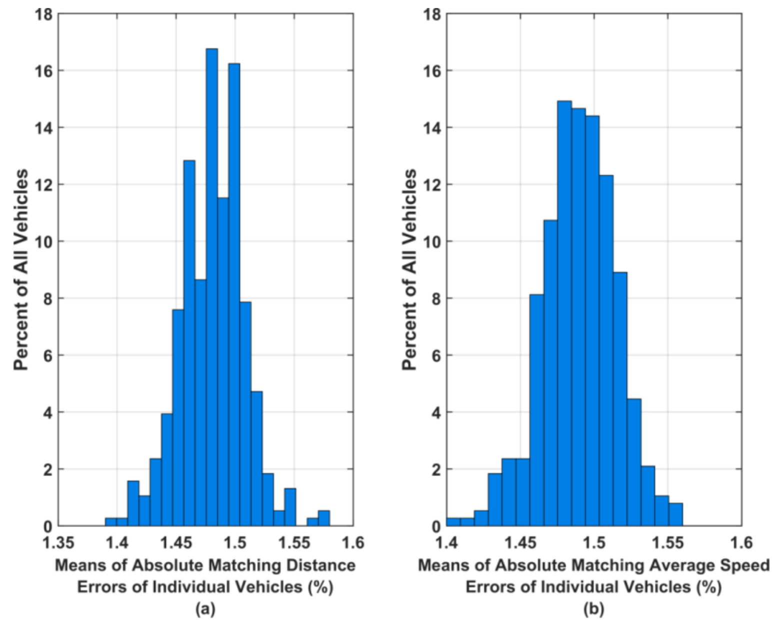


Figure 3.19. Distributions of the means of the absolute matching errors for the PSRC trips after being matched by the ARC trips. a) Distribution of the means of the absolute distance errors. b) Distribution of the means of the absolute average speed errors.

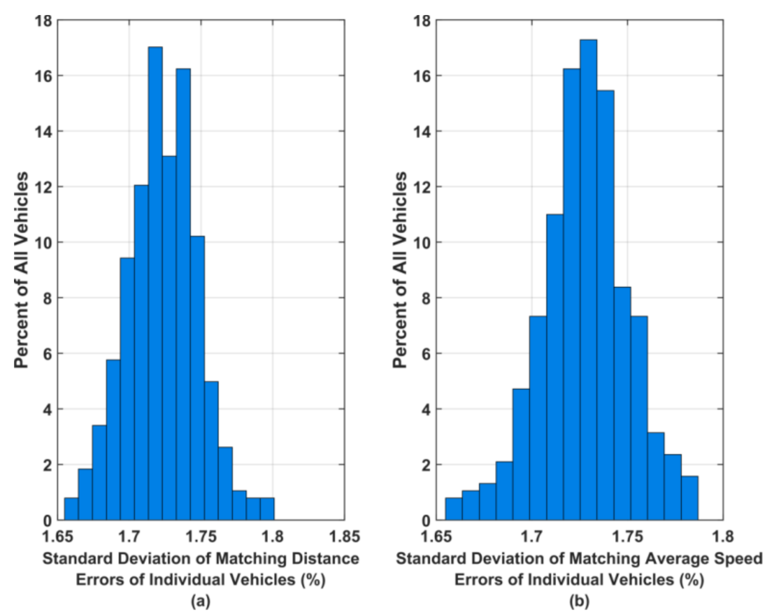


Figure 3.20. Distributions of the standard deviations of matching errors for the PSRC trips after being matched by the ARC trips. a) Distribution of the standard deviations of the distance errors. b) Distribution of the standard deviations of the average speed errors.

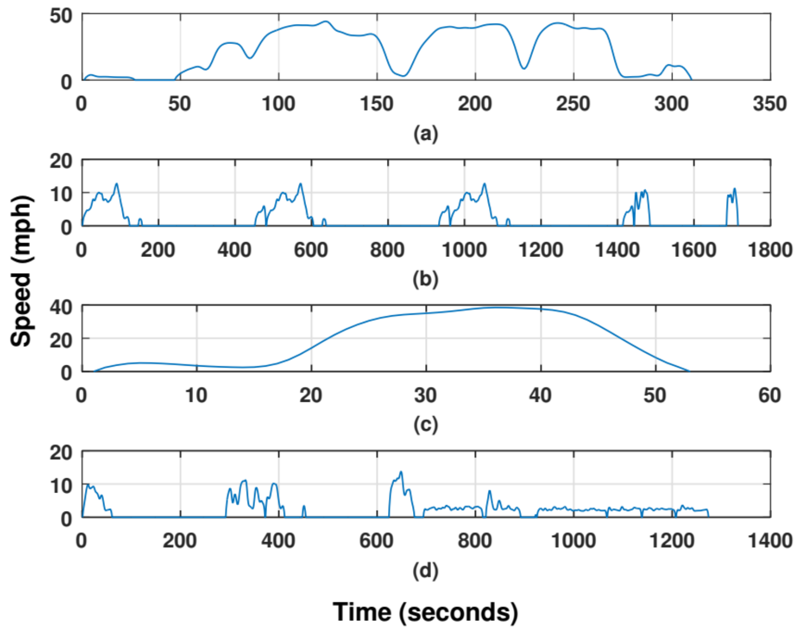


Figure 3.21. Results of matching driving cycles of four different PSRC trips by ARC trips. a) a PSRC trip matched by one original ARC trip. b) a PSRC trip matched by a combination of four original ARC trips. c) a PSRC trip matched by one ARC micro-trip. d) a PSRC trip matched by a mixture of 4 original and 4 ARC micro-trips.

Figure 3.22 shows three different examples of the cycle of the average trip of the generated dataset. The distance of the average trip was 6.8 miles and the average speed was 26.8 mph. The average trip of the generated dataset was determined by averaging the distance of the dataset and choosing trips with an error band of ± 3%. Then, an average speed error band of ± 3% is applied to the average speeds of the chosen trips to choose a pool of trips that match the average trip of the dataset. 667 trips of the dataset matched the average trip and in Figure 3.21 the cycles of only three trips were plotted as examples.

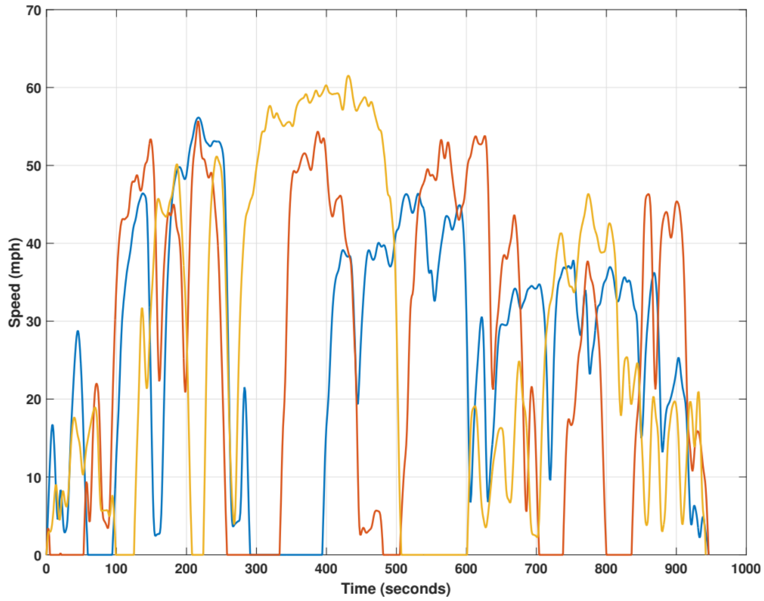


Figure 3.22. Three examples of the cycle of the average trip of the generated dataset.

As an illustration, Figure 3.23 shows the distance-average speed distribution of the 508,447 PSRC trips that were successfully matched by the ARC trips, including the average trip of the dataset, and the distance-average speed distribution of EPA standard drive cycles and European Artemis drive cycles that are listed in Table 1.1. It can be seen that the distance-average speed distribution range of the new dataset covers all of EPA and European Artemis different drive cycles. This indicates that in addition to representing different real-world driving cycles and patterns, the generated dataset still takes into the account and covers the standard driving cycles that are used for fuel economy and gas emissions tests.

To sum up, after matching the PSRC trips with the ARC trips, the final generated dataset has a total of 508,447 trips made on 106,203 driving days of 382 vehicles in one year with a second-by-second velocity profile for each trip. Figure 3.24 shows the distribution of the annual traveled distance for the 382 vehicles of the final generated dataset. The average vehicle of the 382 vehicles traveled 8,790 miles in the one-year selected window. Figure 3.25 shows the monthly distributions of the traveled distance, number of driving days, and number of trips for the total 382 vehicles of the generated dataset. It can be clearly seen from Figure 3.25 that the generated dataset has less number of driving days, total number of trips, and traveled distance in February and March than in the other months. On the other hand, it has more number of driving days, number of trips, and traveled distance in July and August (i.e. in the summer) than in the other months. This can also be noticed from Figure 3.26 which presents the distributions of the total number of daily trips in each month of the year for the 382 PSRC vehicles.

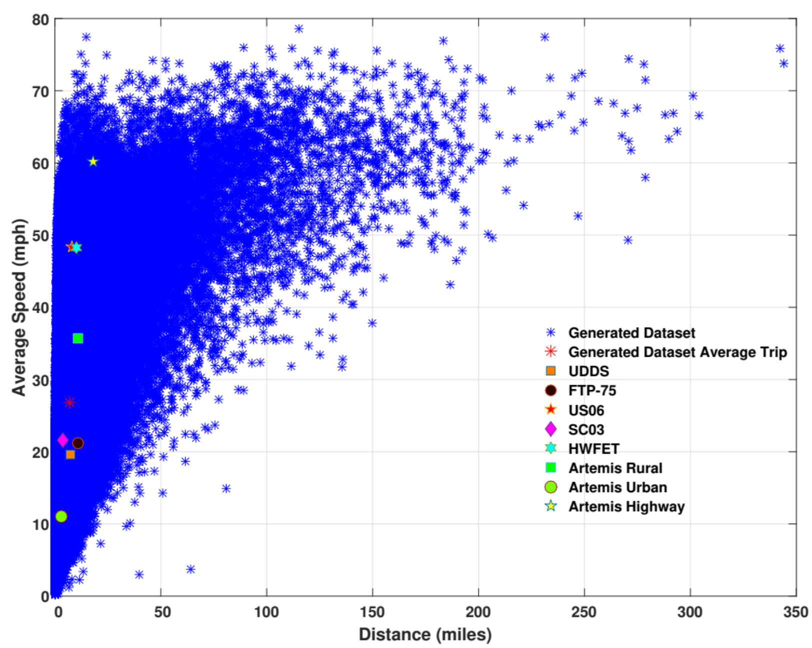


Figure 3.23. Distance-average speed distribution of the 508,447 PSRC trips that were successfully matched by the ARC trips, the generated dataset average trip, and the EPA standard drive cycles and the European Artemis drive cycles that are listed in Table 1.1.

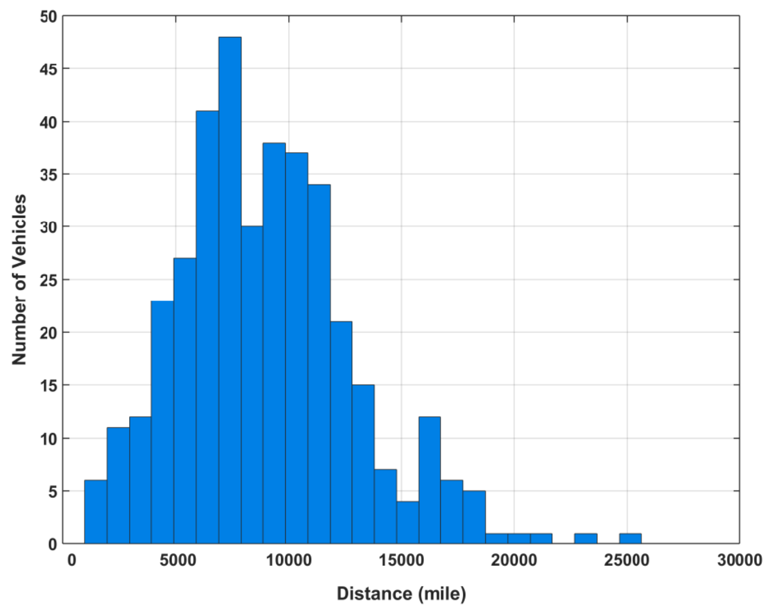


Figure 3.24. Distribution of the annual traveled distance in the best one-year windows for the 382 PSRC vehicles of the final generated dataset.

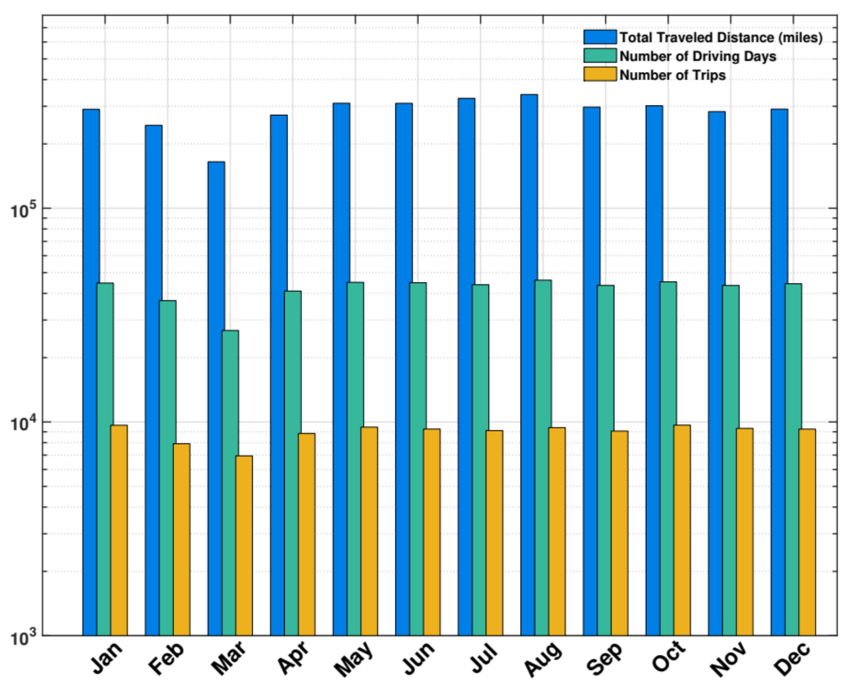


Figure 3.25. Distributions of monthly total traveled distance, number of driving days, and number of trips for the 382 vehicles of the final generated dataset.

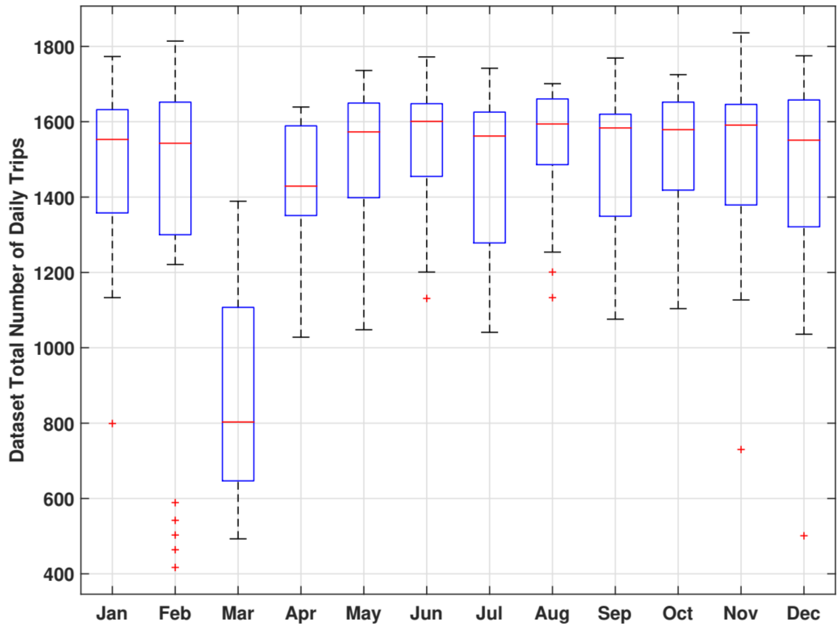


Figure 3.26. Distributions of total number of daily trips in each month of the year for the 382 vehicles of the final generated dataset.

CHAPTER 4

UTILIZATION AND PERFORMANCE OF BATTERY ELECTRIC VEHICLE USING THE GENERATED TRIP DATASET: Method

The objective of the simulation study presented in this chapter is to explore and analyze the performance, utilization, and range limitations of BEV using the trip dataset that I generated in Chapter 2. In this chapter, I first give an overview about the temperature datasets I investigated to be used for this simulation study as the source for the ambient temperature outside the vehicle. Then, I present the overview of the specifications of the simulated BEV (2018 Nissan Leaf), its EPA fuel and range ratings, and the reasons to be chosen for this study. Finally, I present all the steps of my methodology for simulating the one-year driving and non-driving activities of every vehicle of the generated dataset to study the performance and range limitations of the representative BEV throughout one year. The work presented in this and next chapter are reported in my research paper [56].

4.1 Temperature Data

Ambient temperature data play important role in the BEV performance and utility studies. In BEV simulation studies, the ambient temperature at the beginning of every vehicle trip is required to estimate the desired thermal and electrical energy for the climate control system during the trip. It is also required for calculating and monitoring the battery temperature during charging and non-charging parking activities of vehicles and to estimate the battery capacity as the ambient temperature impacts several battery capacity-related characteristics such as the internal resistance and state-of-charge (SOC). Thus, I needed to search the publicly available databases for a temperature dataset that provides hourly temperature data for a large number of geographical locations around the US for a period of one year to be used in this BEV simulation study. The first dataset I was able to find was provided by the National Oceanic and Atmospheric Administration (NOAA) and the second one, which I use in this study, was the TMY3 dataset that was provided by the NREL. In the next two subsections I briefly give an overview about the datasets and discuss the reasons behind choosing the TMY3 dataset for my study.

4.1.1 National Oceanic and Atmospheric Administration (NOAA) Temperature Dataset [57]

The NOAA provides two publicly accessible temperature datasets for hourly temperature and daily average temperature collected in a period of 30 years (1981 – 2010). The hourly temperature dataset contains temperature data of one year collected in 457 weather stations around the US. The temperature data for every hour in these stations is averaged over the 30 years using available data. The daily average temperature dataset provides temperature data for 366 days (February 29 is included) collected in 7,501 weather stations around the US and averaged over the 30 years [58].

The hourly temperature dataset has two main drawbacks. The first one is that the temperature data values for several hours are missing in 198 weather stations. The second drawback is that the number of weather stations that provide hourly temperature data around the US is small compared to the TMY3 dataset. As mentioned above, the dataset provides the hourly temperature data for only 457 geographical locations around the US. Hence, to use this hourly dataset in my study, I needed to consider these two issues because at the time I started my study, the NOAA temperature datasets were the only datasets I was able to find in the public accessible databases. As a result, I applied some interpolation and extrapolation techniques to estimate the missing temperature data in the hourly temperature dataset and to approximate the hourly temperature data at several different locations around the US other than the locations of the 457 provided stations. To improve the accuracy of the interpolation and extrapolation process, the daily average temperature dataset was used to validate the interpolation/extrapolation process.

4.1.2 Typical Meteorological Year Temperature

The NREL provided the Typical Meteorological Year (TMY3) dataset that included numerous weather-related data variables [48]. The TMY3 dataset contains hourly temperature data for 1,020 weather stations at different geographical locations around the US for a period of one year. Figure 4.1 shows the geographical locations of these weather stations on the US map. The dataset is named "typical" because based on some variables and criteria, such as number of missing data, the typical climate data for every month were chosen from a pool of 24 or 15 years of climate data. The temperature data is typical rather than averaged and it may include data for months from different years to represent year-long data for one weather station. Although the data provided by the TYM3 dataset is typical and not averaged as in NOAA dataset, I decided to use it in this study because of some reasons such as not including missing data (the missing data issue has already been handled by NREL [48]), providing hourly temperature data for more geographical locations than NOAA dataset, and the TYM3 has been used by several studies in the literature for BEV studies, such as in [45] – [47].

To study the effect of ambient temperature on the performance and utilization of BEV, six cities around the US with different climates are selected; Los Angeles, Atlanta, Phoenix, Seattle, New York, and Minneapolis. These cities include cold, mild, and hot climates. Weather stations with 24 years of temperature data in these six cities are selected. Figure 4.2 shows the distributions of the hourly temperature in these six cities over the entire typical year [48].

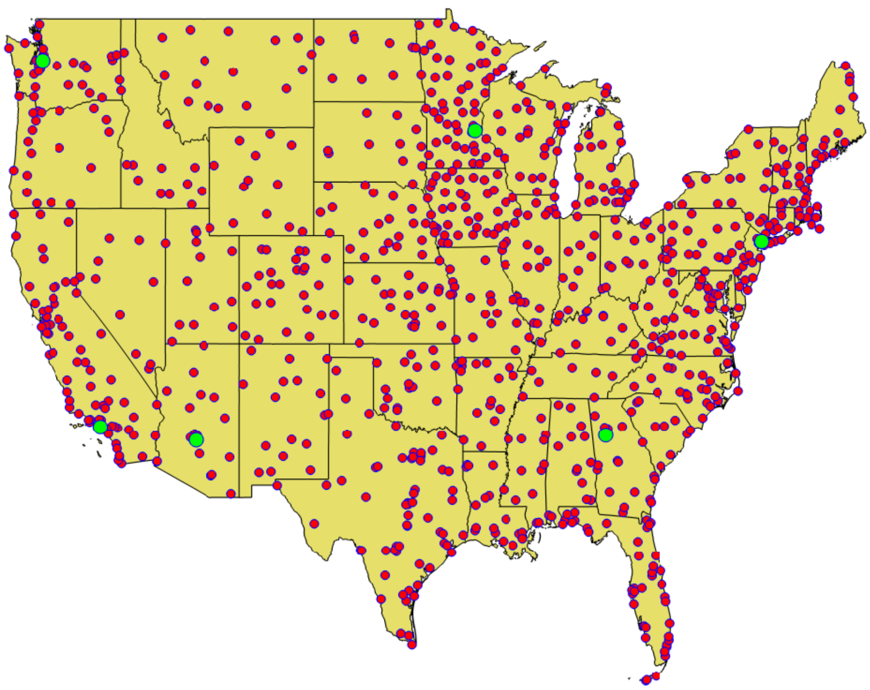


Figure 4.1. Distribution of the geographical locations of the 1,020 weather stations included in the TYM3 climate dataset. Note that the green marks indicate the geographical locations of the six weather stations in the six cities included in this study.

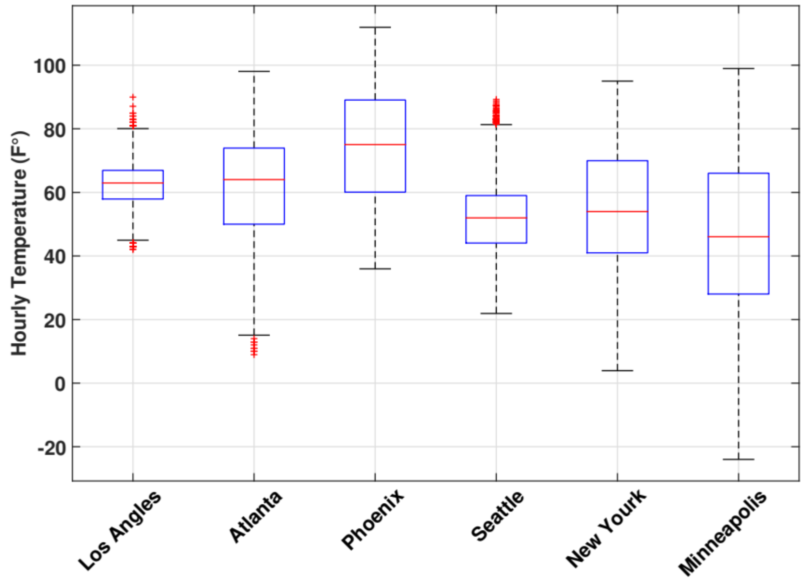


Figure 4.2. Distribution of hourly temperature for the six selected US cities over the typical year.

4.2 Specifications of the 2018 Nissan Leaf

Nissan Leaf is ranked as the world's best seller of BEVs based on the cumulative sales data from 2010 to 2017 [19], [49], [59]. It was also ranked as an affordable BEV in 2018, and has an average EPA rated-range of 151 miles [60]. Nissan makes much more technical information of the Leaf models available to the public as compared to other BEV manufacturers. Even so, for the 2018 model the only testing results available are the final results for range and energy usage tests performed by the EPA and the U.S. Department of Energy (DOE) [61] and [62]. EPA evaluated and tested the 2018 Nissan Leaf and provided the estimated energy consumption/equivalent fuel economy and the range for city (UDDS) and highway (HWFET) standard cycles [61]. Manufacturer's vehicle technical features are presented in Table 4.1 and EPA fuel economy testing results are presented in Table 4.2 [49], [50], [60] – [62]. However, the 2018 model of Nissan Leaf is an upgrade model of the 2013-2017 models and it is helpful to start its modeling by using the data provided for the 2013 model. Several research centers and departments modeled and intensively tested the 2013 model of the Nissan Leaf and made most of their testing data and results available to public [63], [64].

Table 4.1. Specifications of Simulated Vehicle [49], [50].

Maker	Nissan
Model	Leaf
Configuration	FWD
Curb Weight, lbs	3,508
Test Weight, lbs	3,858
Frontal Area, m^2	2.27
Drag Coefficient (Cd)	0.28
Wheelbase, m	2.7
Motor Peak Power, kW	110
Motor Peak Torque, Nm	320
Axel Ratio	8.19
Battery Capacity, kWh	40

4.3 Vehicle Modeling Using ADVISOR

The 2018 Nissan Leaf model is first modeled in ADVISOR [66] and vehicle technical features and parameters are set based on the data provided in Table 4.1. The modeling parameters and settings are adjusted to meet the unadjusted energy consumption values provided by EPA as shown in Table 4.2 at climate control off (72 F°) [61]. Table 4.2 shows the unadjusted and adjusted values for the fuel economy and the total ranges for the city and highway drive cycles for the 2018 Nissan Leaf. The unadjusted fuel economy values are provided by the US DOE [62]. Because their tests are carried out on dynamometers instead of actual roads, EPA uses an adjustment factor of about 0.7 to adjust fuel economy results to reflect the effect of real-world impacts on BEV's fuel economy [65]. Because in this study I simulate real-world passenger vehicles' trips with real-world drive cycles and actual trip's details and I also include in this simulation most of the parameters that influence the fuel economy of a BEV, such as the ambient temperature and battery temperature, I expect that the results of this simulation should take into the account the impact of all these parameters and these results should be comparable to EPA adjusted values for fuel economy and total range.

Table 4.2. Results of the tests carried by the EPA and the DOE on the 2018 Nissan Leaf [60]- 62].

	adjusted		unadjusted			
	MPGe	Range (miles)	AC Energy (Wh/mile)	DC Energy (Wh/mile)	*RAF	Range (miles)
City Cycle (UDDS)	124	-	193.689	170	0.8777	231.462
Highway Cycle (HWFET)	100	-	238.837	209	0.8751	187.709
Combined	112	151	-	-	-	-

*RAF: Recharge Allocation Factor = Net DC consumed energy / AC charged energy

Because I couldn't find the information on the efficiency of the motor and the inverter of the modeled vehicle, these efficiencies were estimated with the data on the efficiencies of the 2013 Nissan Leaf provided by the US DOE and Argonne National Laboratory [63] - [64]. The 2013 model was intensively tested and modeled by several research centers and the motor of the 2018 model can be considered as an upgrade of the previous Nissan Leaf models.

4.4 Simulation Process

The main steps of the simulation process are shown in Figure 4.3. The process is applied to every PSRC vehicle starting with the first trip in the one-year window of trips and ending with the last trip of the window. For every trip of a PSRC vehicle, the process starts by getting the ambient temperature of the specified geographical location at the start time of the trip from the temperature dataset. The temperature at every second between the hours is achieved using linear interpolation. Since ADVISOR only allows to set the value of the ambient temperature at the beginning of the trip, the temperature variation during the trip simulation is not considered. Then, ADVISOR is initialized with the ambient temperature, the initial temperature values for the battery and the motor, and the auxiliary power required after being calculated as shown later in the next subsection. For the first trip of the vehicle, the initial temperature for the battery and motor is set to the value of the ambient temperature at the beginning of the trip while for all next trips the initial temperature values of the battery and motor are set to the final temperature values after the soak time of the previous trip. Soak time of a trip is the time duration when a vehicle is off before starting the next trip.

After initializing ADVISOR with the required parameters, the ADVISOR simulator is run with the drive cycle of the trip. ADVISOR simulator calculates the energy required to maintain the target vehicle speed at every second and drain this energy from the battery. The simulator automatically terminates if the SOC of the battery reaches 0.2 (20%) at any time of the drive cycle simulation. To consider the Leaf’s long-life mode, I assume the battery is allowed to discharge until it reaches 20% of its overall capacity (SOC > 0.2). If the end SOC is less than or equal to 0.2, even if the trip was completely simulated, the trip is considered as an uncovered trip and the initial battery SOC is reset to its value before simulating this uncovered trip. If the trip was completely simulated by ADVISOR and SOC > 0.2, the trip is listed as a covered trip and the total DC and AC consumed energies and the miles per gallon equivalent ($MPGe$) are calculated from the battery available power (power consumed during the trip) as shown in Eqs. 4.1 to 4.4.

$$E\_DC = \int P_{battery}\, dt \tag{4.1}$$

$$EC\_DC = \frac{E\_DC}{Distance \times 3600} \tag{4.2}$$

$$EC\_AC = \frac{EC\_DC}{RAF} \tag{4.3}$$

$$MPGe = \frac{33{,}705}{EC\_AC} \tag{4.4}$$

where E_DC is the total energy used in Joules, $P_{battery}$ is the power provided by the battery during a trip, EC_DC is the DC energy consumption in Wh/mile, $Distance$ is the trip traveled distance in miles, EC_AC is the AC energy consumption in Wh/mile, RAF is the Recharge Allocation Factor and is set to 0.877 based on the EPA tests [61], $MPGe$ is miles per gallon gasoline-equivalent, and the constant 33,705 is the energy density of the gasoline in Wh/gal (1 gallon gasoline = 33705 Wh) [62].

The next step is to check for the possibility of recharging the battery. The battery is recharged only if the destination of the simulated trip is to-home, the destination of the next trip is from-home, and the soak time of the simulated trip is greater than or equal to 30 minutes. The soak time here is the time duration between the end of the simulated trip and the beginning of the next trip. The battery recharging event may take place after simulating the trip even if the trip was not covered. The battery recharging process is discussed in full details later in this section. Finally, the temperature of the battery and motor at the end (just one second before the start of the next trip) of the trip's soak time are calculated to be used as the initial temperature values for the next trip. The battery temperature estimation is presented later in the battery thermal behavior subsection while the motor temperature is estimated using a simple exponential model as shown in Eq 4.5 considering all heat rejected to the environment by the motor.

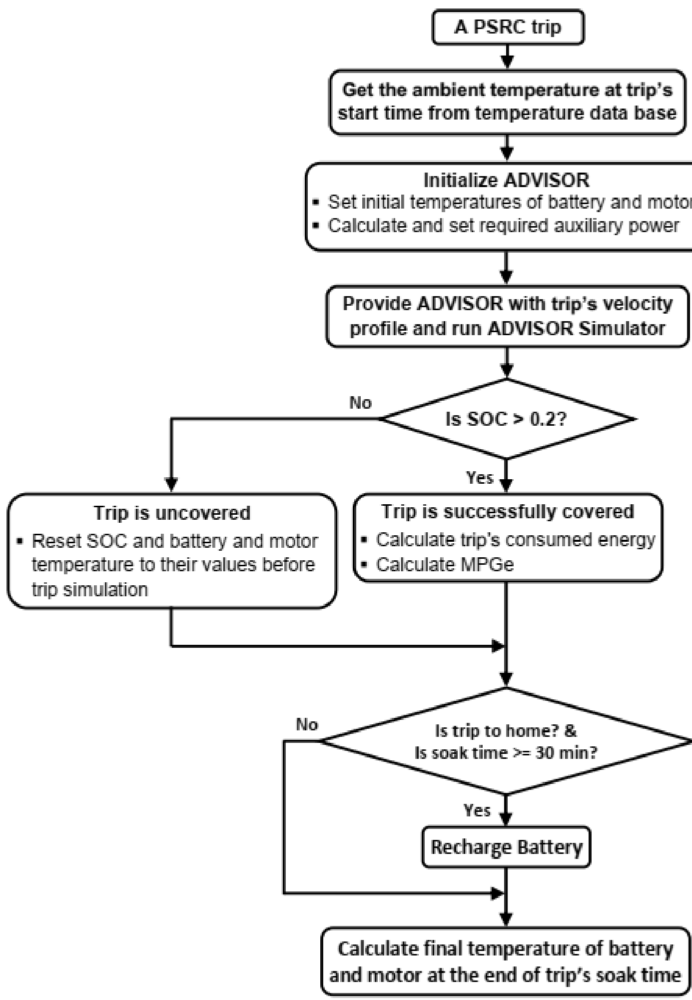


Figure 4.3. Main process for simulating vehicle activities for the 376 selected PSRC vehicles.

$$T_{motor}(t) = T_{amb}(t) + (T_{motor}(t-1) - T_{amb}(t)) \times e^{-\frac{1}{\tau}} \quad (4.5)$$

where $T_{amb}(t)$ is the ambient temperature at current time and τ is the motor cooling time constant which is set based on the assumption of the cold soak for the motor which is assumed to be eight hours.

4.4.1 Auxiliary Power Used by the Nissan Leaf

To calculate the auxiliary energy at the beginning of each trip at ambient temperature, I use the method proposed in [47]. In this method, the auxiliary power is divided into two parts; the first part is the energy consumed by the climate control system and the other part is the energy consumed by other vehicle's components. The power consumed by climate control system is calculated as shown below:

$$P_{thermal} = K \times |T_{outside} - T_{inside}| \quad (4.6)$$

$$T_{inside}(C°) = \begin{cases} 20, & T_{outside} \leq 20 \\ T_{outside,} & 20 < T_{outside} < 24 \\ 24, & 24 \leq T_{outside} \end{cases} \quad (4.7)$$

$$P_{aux\ (electric)} = \begin{cases} \frac{P_{thermal}}{COP_{heat}} + P_{other}, & T_{outside} \leq 20 \\ P_{other}, & 20 < T_{outside} < 24 \\ \frac{P_{thermal}}{COP_{AC}} + P_{other}, & 24 \leq T_{outside} \end{cases} \quad (4.8)$$

where $P_{thermal}$ is the thermal power generated by vehicle climate control system, K is the thermal conductivity of vehicle and is taken to be 350 W/C° [47], $T_{outside}$ and T_{inside} are the ambient temperatures outside and inside the vehicle respectively, P_{aux} is the total electrical power consumed by vehicle auxiliary system, COP is the Coefficient of Performance and the values of COP for the AC, COP_{AC}, is set to 2.5 and for the heater, COP_{heat}, it is set to 3 as suggested in [47], P_{other} is the non-climate auxiliary electrical power and is set to 250 Watts and I assume that this part is always available during the trip simulation while the key is on. It is assume that both climate control power and other auxiliary power are not available during the parking events (key is off) even if the parking event includes battery charging activity.

4.4.2 Battery Recharging

The strategy for recharging the battery is basically based on the destination of each trip of the vehicle. As mentioned in Chapter 2, one of the advantages of the PSRC dataset is the detailed information about tours and trips destinations. The trips of each vehicle were categorized by the original survey into four different tours: home-to-home, home-to-work, work-to-work, and work-to-home tours. I assume that the driver always recharges the battery only at home and based on the mentioned tours categories, the recharging events only take place after the last trip of home-to-home or work-to-home tours (i.e. the trip's destination is to-home). So, rather than limiting the recharge events to the end of every driving day as most studies in the literature suggest, I assume the driver will always recharge the battery after each to-home trip if they intended to stay home for at least 30 minutes (trip soak time ≥ 30 minutes).

Figure 4.4 shows the distribution of percent of to-home trips to the total number of trips in the one-year window for the 382 vehicles of the generated trip dataset. The PSRC vehicles that had a percent of to-home trips less than 15% are excluded from this study. The percent of to-home trips in these vehicles is small (compared to the average vehicle) and this means that based on the proposed charging strategy, less battery charging events will take place and the BEV will not cover most of the vehicles' activities. It can be noticed from Figure 4.4 that six vehicles in the dataset are excluded from this study and 376 PSRC vehicles are used. The average PSRC vehicle had about 32% of its trips in the one-year window as to-home trips. Figure 4.5 shows the distribution of the percent of the driving days that their last trip was to-home trip to the total number of the driving days in the one-year window of trips for the 376 PSRC selected vehicles. It can be noticed from Figure 4.5 that for most of the selected PSRC vehicles the last trip of most of the driving days was to-home trip where the average was 90.51%. This indicates that the proposed battery recharging strategy also includes charging events at the end of every driving day which was proposed by all other studies.

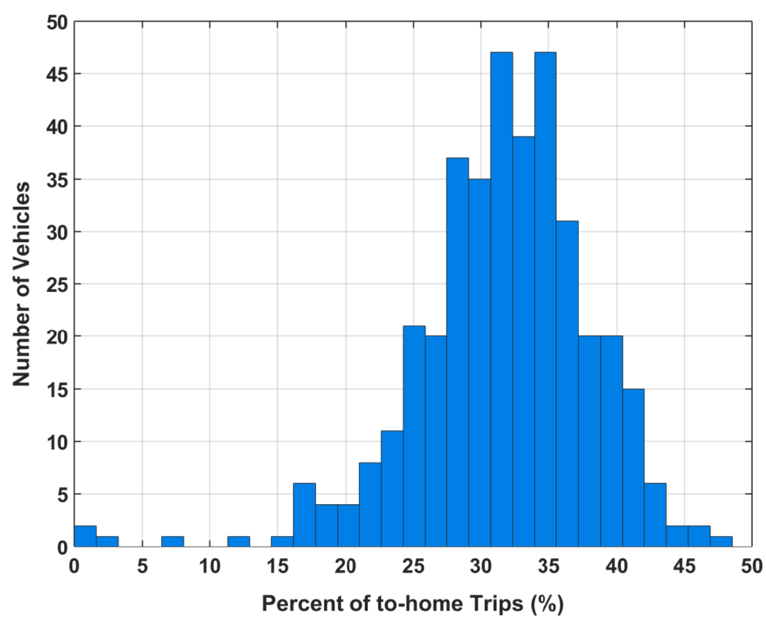


Figure 4.4. Histogram of percent of to-home trips to the total number of trips of the vehicle in the one-year window of trips for the 382 PSRC targeted vehicles.

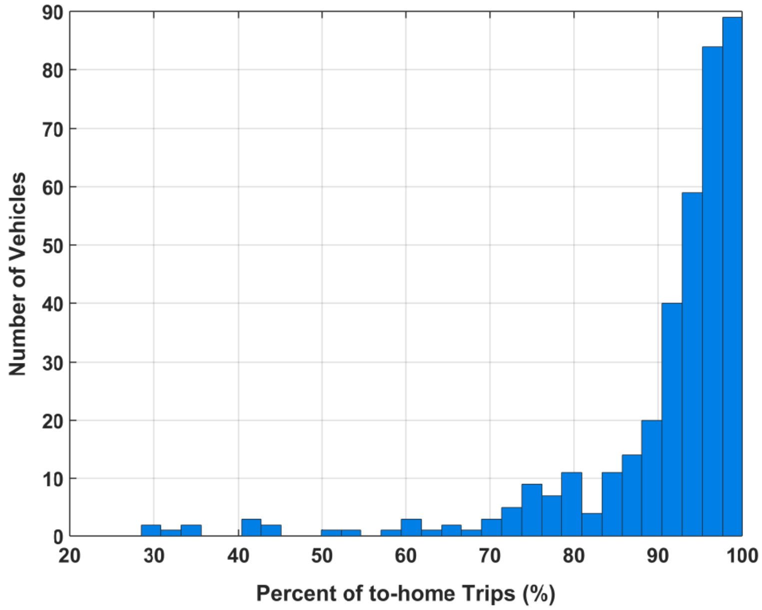


Figure 4.5. Histogram of the percent of driving days that their last trip was to-home trip to the total number of driving days of the vehicle in the best one-year window for the 376 PSRC targeted vehicles.

Using this charging strategy makes this simulation study quite close to the reality. It is assumed the charger is only available at home and drivers will not charge the battery if they are staying home for a short time. We cannot ensure that the driver will be able to charge off-home because of such factors as location, availability, and occupancy of off-home charger. My charging strategy also considers automaker’s recommendations for battery recharging - charging the battery more frequently and in smaller amounts to avoid battery overheating and also to keep the battery always at high charging status which may prolong the battery life [49], [50].

For the battery charger, I assume that the driver only uses the regular level 2 charger that delivers up to 6.6 kW of power with a supply voltage of 240 V AC and the charger can be accessed only at home. The charger efficiency is set to 87% as a constant based on the tests carried by EPA [61]. The charging simulation is performed in a one-second time step. The charging current is assumed to be constant.

It is assumed that the battery is only allowed to be depleted to 20% of its overall capacity. This means that the longest battery recharging event takes place when recharging the battery from 20% to 100% of its overall capacity (from 0.2 SOC to 1 SOC). Battery recharging duration is always restricted by the trip soak time as shown in Eq 4.9.

$$\text{battery recharging duration } \leq \text{trip soak time} \tag{4.9}$$

4.4.3 Battery Thermal Behavior

In this BEV simulation study, I take into the account the thermal behavior of the battery during both charging and non-charging parking events. During battery recharging events, the actual charging behavior is simulated and the parameters that influence the charging efficiency are all considered. One of the main parameters is the battery temperature. The battery temperature during the charging process needs to be calculated to estimate some other parameters that depend on the battery temperature such as battery internal resistance and open circuit voltage and these parameters are required for estimating battery SOC. Also, calculating the battery temperature during charging events is required for estimating the battery temperature at the beginning of the next simulated trip. When the battery is being charged, three major heat components must be considered, ignoring the heat component generated by the gradient of concentration [67], [68]. The first two components are the reversible and irreversible heat generations and the third heat component is the heat rejected to the environment [67]. The change in battery temperature is calculated every second during the charging process using the aforementioned three heat components. The irreversible heat generation (q_{irr}) is calculated as shown in Eq. 4.10 as proposed by ADVISOR and the reversable heat generation (q_{rev}) is estimated as shown in Eq. 4.11 based on the studies in [67], [68].

$$q_{irr} = I^2 \times R_{in} \tag{4.10}$$

$$q_{rev} = -I \times T(k) \times \frac{\Delta U}{\Delta T} \tag{4.11}$$

where I is the charging current, R_{in} is considered as the battery internal resistance at $T(k-1)$, $T(k)$ is the current battery temperature, ΔU is the change in the battery open circuit voltage, and ΔT is the change in battery temperature. R_{in} and ΔU are interpolated from temperature dependent predefined vectors proposed by the battery model based on $T(k-1)$, $T(k-2)$, $SOC(k-1)$, and $SOC(k-2)$. $\frac{\Delta U}{\Delta T}$ is the entropic coefficient [67].

The amount of heat rejected to the environment, (q_{rej}), is estimated using a simple exponential model to calculate temperature change as shown in Eq 4.12.

$$q_{rej} = m \times c_p \times [T(k-1) - (T_{amb}(k) + \left(T(k-1) - T_{amb}(k)\right) \times e^{-\frac{1}{\tau}})] \tag{4.12}$$

where m is the battery mass, c_p is the battery cell specific heat, $T_{amb}(k)$ is the current ambient temperature, τ is the battery cooling time constant which is set based on the assumption of the cold soak for the battery which is assumed to be eight hours.

Therefore, the battery temperature is approximated every 1 second time step as shown below:

$$mc_p \Delta T = \ q_{irr} + q_{rev} \ - \ q_{rej} \tag{4.13}$$

$$\Delta T = T(k) - T(k-1) \tag{4.14}$$

$$T(k) = \frac{q_{irr} - q_{rej} + m \times c_p \times T(k-1)}{m \times c_p + I \times \frac{\Delta U}{\Delta T}} \tag{4.15}$$

In case the required charging time is less than the trip's soak time, the battery temperature change from the end of the charging event to the end of the trip's soak time is calculated by only considering the heat rejected to the environment, q_{rej}, and battery temperature is calculated as shown in Eq. 4.16. This is also applied to the cases when no charging event takes place during parking activities by calculating the battery temperature change throughout the trip's soak time (parking time with key off).

$$T(k) = T_{amb}(k) + (T(k-1) - T_{amb}(k)) \times e^{-\frac{1}{\tau}} \tag{4.16}$$

In the battery thermal behavior simulation, battery cooling/warming during battery charging events and battery warming during the non-charging parking events are also considered. As stated by the automaker in [49], [50], the battery is cooled at high temperatures and warmed at low temperatures. For cooling the battery during charging events, Nissan Leaf uses a cooling fan that automatically turns on at a specific temperature. I set this temperature as suggested by ADVISOR to 35 °C as it is not defined by the automaker and its power consumption rate is set to 300 Watts. So, for every second of charging the battery, the charging power rate is decreased by $\frac{300}{3600}$ Watts to consider the power consumed by the cooling fan if the battery's current temperature is greater than or equal to 35 °C and the change in the battery thermal energy due to the effect of the cooling fan is calculated as presented by ADVISOR in [69]. For warming the battery in cold weather, Nissan Leaf uses a battery warmer that automatically turns on during both charging and non-charging parking events when the battery temperature reaches -17 °C and automatically turns off when battery temperature increases to -10 °C [49], [50]. During charging events the warmer uses electrical power from the charger, but during non-charging events it uses electrical power from the battery if the battery SOC is greater than or equal to 15% [49], [50]. I assume that at non-charging parking events, when battery SOC is less than or equal to 15%, the battery warmer does not turn on and the minimum battery temperature is set to -20 °C. On the other hand, if the battery warmer turns on during a charging parking event, the energy it consumes is always drawn from the charger only. The battery warmer is assumed to consume energy at a power rate of 300 Watts and all this electrical power is assumed to be converted into thermal power. So, for every second of simulation time step, the battery charging power rate is decreased by $\frac{300}{3600}$ Watts to consider the power consumed by the battery warmer within the specified range of battery temperature and the battery thermal energy is increased by $\frac{300}{3600}$ Watts.

4.5 Range Simulation

As mentioned above, in the main simulation procedure shown in Figure 4.3 the battery is assumed to be recharged after each to-home trip if the customer intended to stay home for at least 30 minutes (soak time ≥ 30 minutes). This battery recharging strategy does not allow to simulate the battery range for the vehicles of the dataset. According to EPA testing procedures, the battery range is calculated by fully charging the battery and then driving the vehicle in specified, or unspecified, driving cycles until the battery is completely depleted (i.e. the battery is not able to provide enough energy to the motor to move the vehicle). Hence, to simulate the battery range for all the vehicles of the dataset, the same steps of the main simulation procedure are followed except the charging step. For every vehicle, the simulation starts with the first trip with battery SOC = 1 and goes through the trips in sequence until the battery is completely depleted (i.e. until ADVISOR terminates the cycle simulation when the battery provided energy is not enough to handle the required energy for the drive cycle). Then, the battery range is calculated by summing up the traveled distances of the trips that were covered by the battery cycle. To start the next battery cycle, the battery is fully recharged again (SOC = 1) and the simulation process is restarted with the trip next to the last covered trip in the previous battery cycle and the same procedure is repeated until all the trips of the vehicle are simulated. If the last trip of a battery cycle was not completely covered, the amount of distance of this trip covered by this battery cycle is accounted towards this battery cycle and this trip will be simulated again in the next battery cycle. This procedure is applied to all vehicles of the dataset in the simulation of the six selected US cities.

CHAPTER 5

UTILIZATION AND PERFORMANCE OF THE 2018 NISSAN LEAF USING THE GENERATED TRIP DATASET: Simulation Results

The results of the BEV simulation study discussed in Chapter 4 are presented here in this chapter. The results demonstrate the effect of the battery recharging strategy on the BEV to meet driver's driving requirements as well as the negative influence of the temperature on the performance of the BEV.

Figure 5.1 shows the distribution of the total number of uncompleted driving days in the six cities. A driving day is considered as uncompleted if either all or some of the trips on this day were not covered. As expected, the simulated BEV was able to cover more driving days in the cities with mild annual average temperatures, such as Los Angeles, than in the cities with cold and hot annual average temperatures, such as Minneapolis and Phoenix. The total number of uncompleted driving days in Los Angeles is 4,269 days for the 376 PSRC vehicles out of the 106,203 total driving days in the one-year period while in Minneapolis it is 5,507 days. As shown in Figure 5.2, the number of driving days that the simulated BEV could not complete for the average vehicle is 12 days in Los Angeles while in Minneapolis it is 14 days. Averaged over the six cities, the activities of 15% of the 376 PSRC vehicles can be completely covered by the representative BEV with my proposed battery recharging policy.

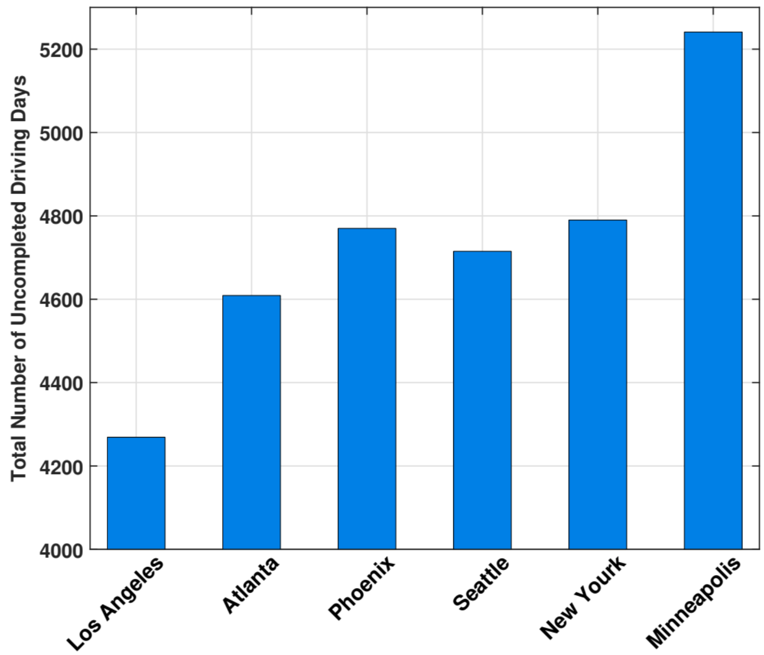


Figure 5.1. Distribution of total number of uncompleted driving days of the 376 PSRC vehicles in the one-year period for the six selected US cities.

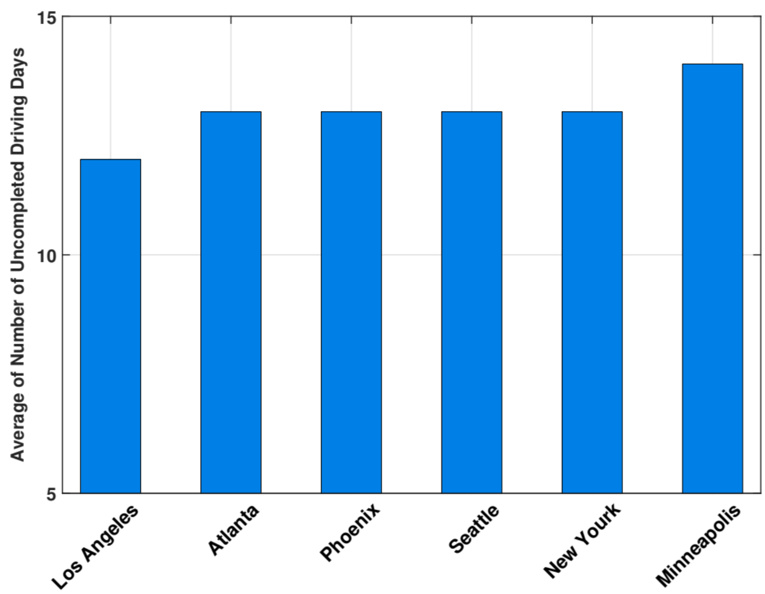


Figure 5.2. Distribution of the average of number of uncompleted driving days of the 376 PSRC vehicles for the six selected US cities.

Figure 5.3 shows the distribution of uncompleted driving days for the 376 PSRC vehicles in Los Angeles and Minneapolis. Figure 5.4 shows the distribution of percent of uncompleted driving days to the total number of driving days for each PSRC vehicle. The average percent of uncompleted driving days for Los Angeles is 3.94% while for Minneapolis it is 5.15%. The results in Figure 5.3 and 5.4 show the effect of battery recharging strategy for the BEV on the activities that can be replaced with the simulated BEV besides the effect of the temperature and other factors.

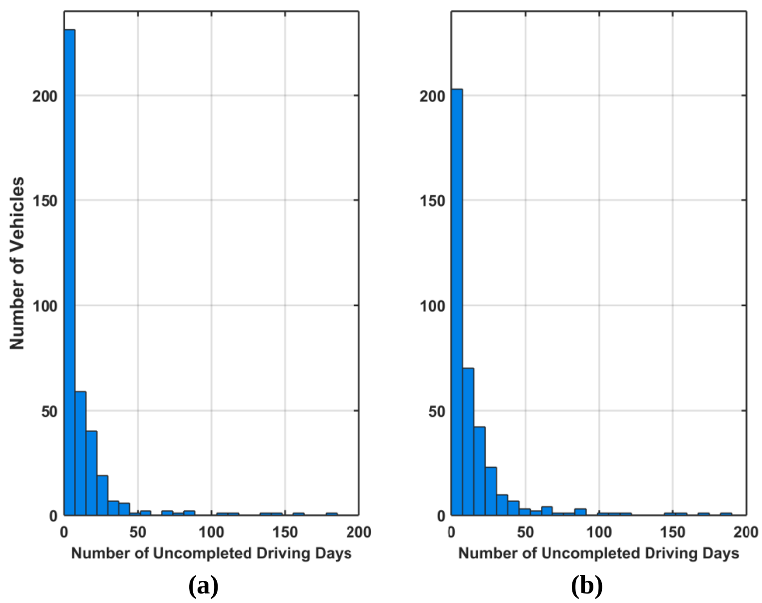


Figure 5.3. Distribution of number of uncompleted driving days in the one-year period for two cities. a) Los Angeles. b) Minneapolis.

Figure 5.5 shows the average of accumulated fuel economy in the six cities. The average fuel economy is calculated by taking the average of the accumulated fuel economy (MPGe) for the covered trips of the 376 PSRC vehicles in each city. The results indicate the significant influence of temperature on fuel economy of BEV. It can be seen that in Los Angeles, where less auxiliary energy is required, the average of accumulated MPGe is

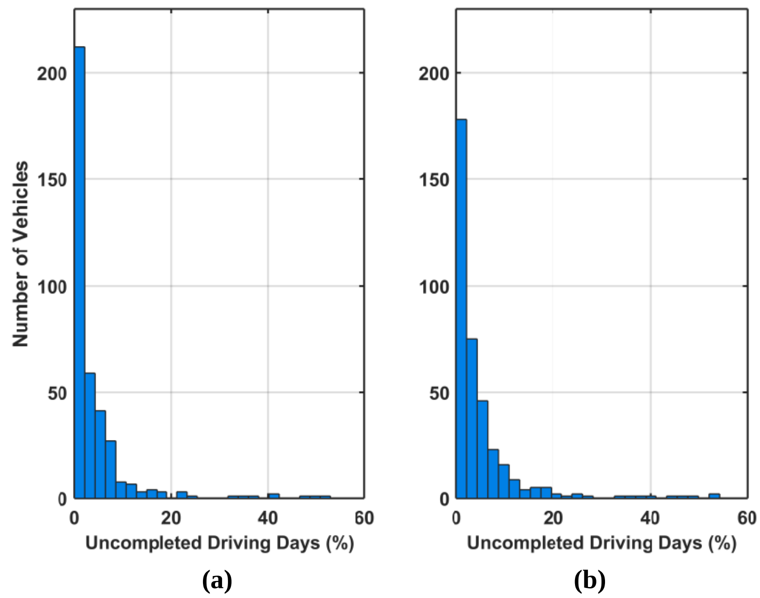


Figure 5.4. The corresponding distributions of percent of uncompleted driving days shown in Figure 4.8. a) Los Angeles. b) Minneapolis.

about 131 while in Minneapolis, where more auxiliary energy is required, it is about 97. The average of the accumulated MPGe for the six cities is 112.33. A close match of these values with the EPA figures is not expected because EPA calculates the average of combined fuel economy differently. EPA calculates the combined fuel economy by averaging the weighed city and highway fuel economy values. The city MPGe value is weighed by 55% and the Highway MPGe value is weighed by 45% [62]. However, the average of the accumulated MPGe of the six cities in this study appears to be slightly high compared to the results in [47] because the dataset used in this study tends to have more city trips than highway trips. The average of trip average speeds is about 24 mph and this is closer to the average speed of the city drive cycle (UDDS) than the highway drive cycle (HWFET) used by EPA. The average speed of the UDDS cycle is 19.59 mph while it is 48.30 mph for the HWFET cycle.

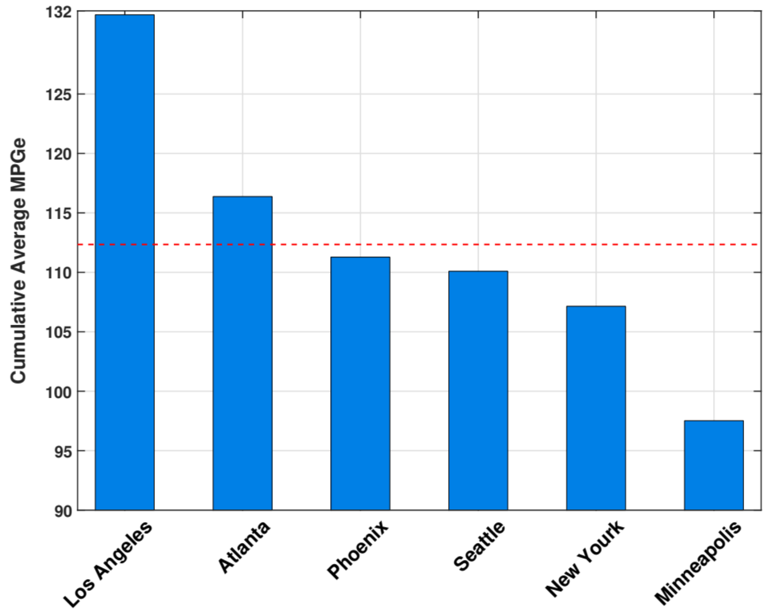


Figure 5.5. Distribution of cumulative average MPGe for the six US cities. The red dotted line shows the average fuel economy of the BEV in the six cities which is 112.33 MPGe.

Comparing the results shown in Figures 5.1 and 5.5 achieved by the BEV in the six cities, it can be noticed that the BEV could cover more driving days throughout the period of one-year for the entire dataset in Seattle than it could cover in Phoenix although it had better fuel economy (more MPGe) in Phoenix than in Seattle (the MPGe for the BEV in Phoenix is greater than in Seattle by about 1.2). The reason behind this might be because basically the BEV in Seattle will miss more driving days in cold seasons than in hot and mild seasons and the opposite is true for Phoenix and as shown in Figure 3.10 the used dataset has less driving days in the cold season than in the mild and hot seasons. This can also be noticed in Figures 5.6 and 5.7. where Figure 5.6 shows the distribution of total number of uncovered driving days per month for the 376 vehicles of the generated dataset in Phoenix and Seattle while Figure 5.7 shows the distribution of the difference between the total number of uncovered driving days per month for the same 376 in Phoenix and

Seattle (total number of uncovered driving days per month in Phoenix - total number of uncovered driving days per month in Seattle). Hence, overall the year period, the BEV uncovers more driving days in Phoenix than it does in Seattle.

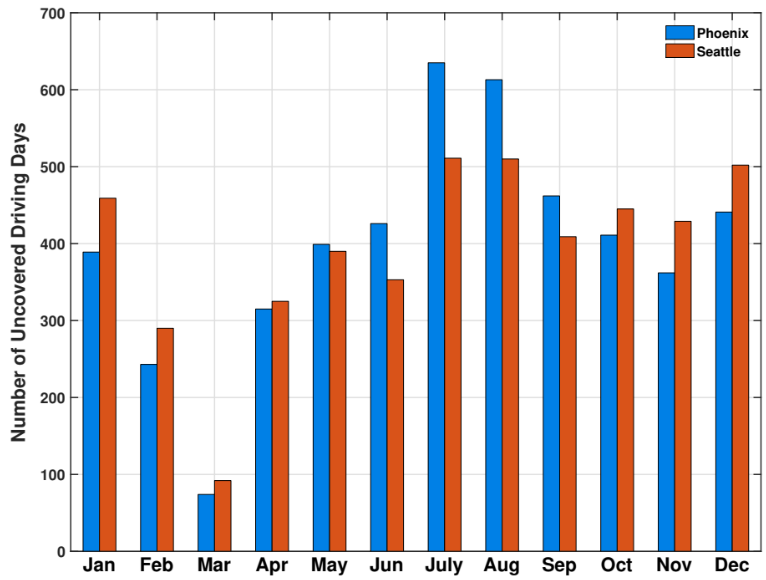


Figure 5.6. Distributions of total number of uncovered driving days per month for the 376 vehicles of the generated dataset in Phoenix and Seattle.

The distribution of the AC electrical energy consumed by the 376 PSRC vehicles in the one year period in the six cities is shown in Figure 5.8. The annual electrical energy in this figure includes the AC electrical energy required for the drive cycles of the covered trips, battery cooling during charging events, and battery warming during charging and non-charging parking events (the latter only applies to Minneapolis). The average vehicle in Los Angeles requires 2.13 MW of electrical energy annually while the average vehicle in Minneapolis requires about 2.68 MW. It is noticed that the average vehicle in Phoenix requires slightly more annual energy than the average vehicle in Seattle although the MPGe in Phoenix is better than that in Seattle. The reason is that the BEV in Phoenix requires more annual energy for battery cooling during the charging parking events than in Seattle. Figure 5.9 shows the distribution of the daily AC electrical energy consumed by the covered trips of the 376 PSRC vehicles in Los Angeles and Minneapolis. It is noticed that even in a city with low fuel consumption (high MPGe) such as Los Angeles, the simulated BEV with the proposed battery charging strategy could not cover the driving days that require large amounts of energy. The maximum daily energy can be covered with the simulated BEV in Los Angeles is 57.1 kWh. This supports the need for the fast charging.

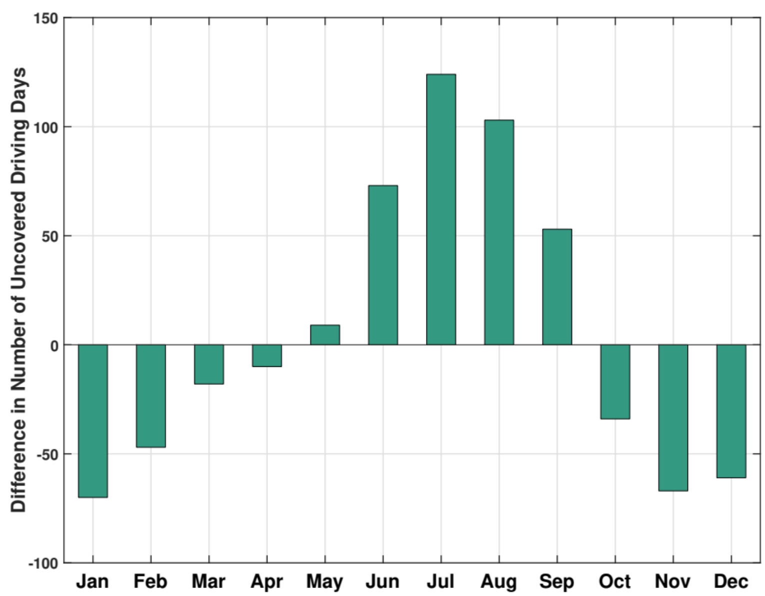


Figure 5.7. Distributions of the difference between the total number of uncovered driving days per month for the 376 vehicles of the generated dataset in Phoenix and Seattle.

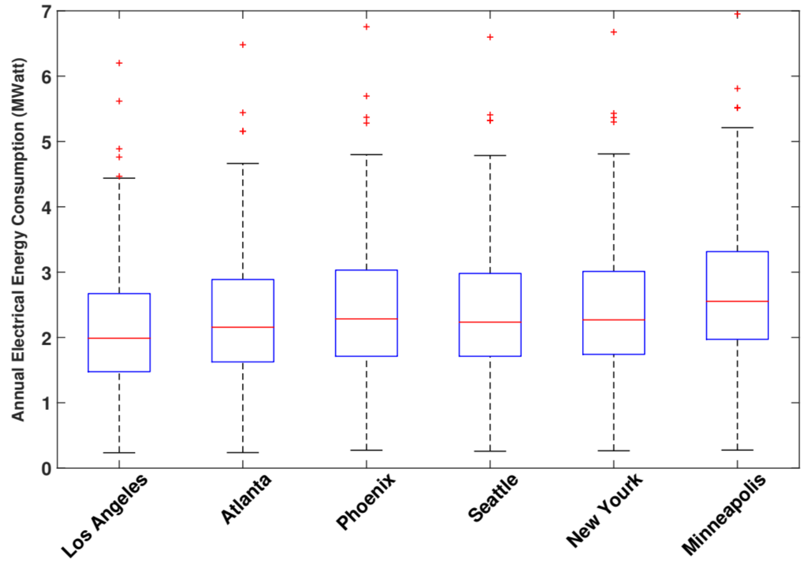


Figure 5.8. Distribution of the annual electrical energy consumption for the 376 PSRC vehicles simulated in the six US cities. This plot does not count the trips uncovered due to the charging strategy.

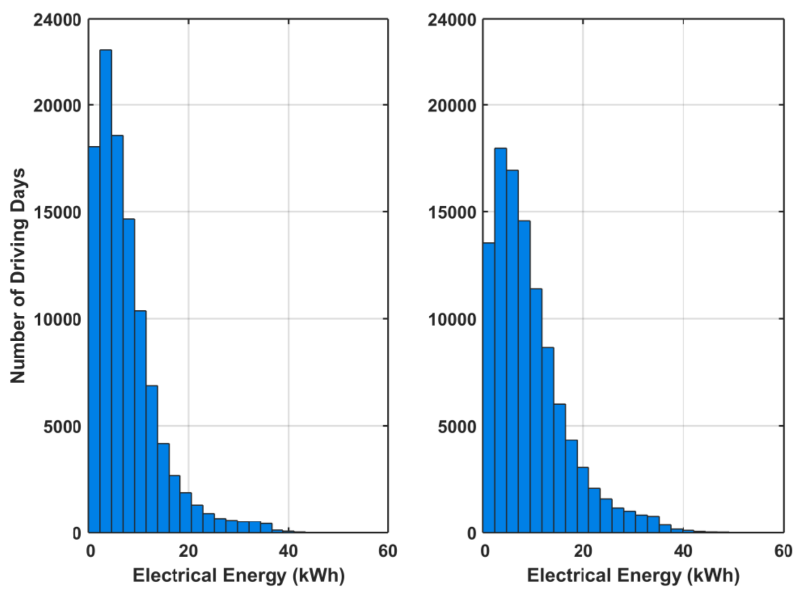


Figure 5.9. Distribution of the daily energy consumption of the fully-covered and partially-covered driving days for the 376 PSRC vehicles for two cities. a) Los Angeles. b) Minneapolis.

The results of range simulation are presented in Figure 5.10, which indicate the variations in the range throughout the cities based on the fuel economy of the simulated

BEV in each city. The average range for Los Angeles (mild annual average temperature) is about 174.2 miles while for Minneapolis (cold annual average temperature) it is about 130.6 miles. The average range for the six cities is 148.5 miles which is very close to the EPA values. It can be noticed from Figure 5.10 that in Minneapolis the BEV range was low in some cases compared to the other cities and this is due to the effect of cold temperatures. Besides the negative impact of the cold temperatures on BEV fuel economy and on battery capacity and efficiency, the sever cold temperatures (temperature ≤ -17 C°) lead to energy consumption by the battery warmer from the battery to keep it warm during non-charging parking events. In some long parking events in severe cold temperatures the battery warmer consumed about half of the battery energy to keep it warm.

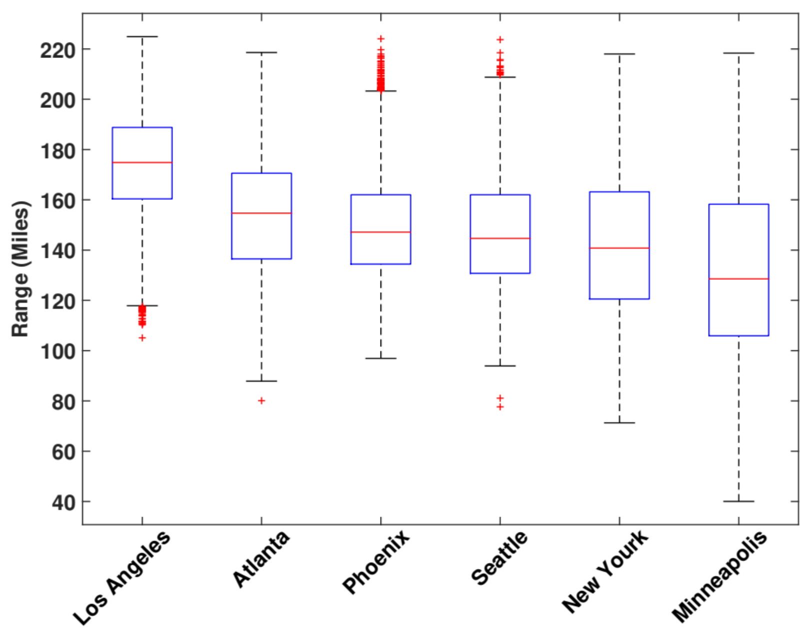


Figure 5.10. Distribution of range in the six US cities.

Figure 5.11 shows the distribution of the annual AC electrical energy required to cover all the trips of the 376 PSRC vehicles and their parking events in the six cities. The average vehicle in Los Angeles requires 2.31 MW of electrical energy annually while the average vehicle in Minneapolis requires 3.18 MW. The distributions of the daily electrical energy required to cover all the trips on all the driving days of the trip dataset in Los Angeles and Minneapolis are shown in Figure 5.12. It can be seen that the dataset has some driving days that require electrical energy beyond the battery capacity of the simulated BEV and this means that even with fully recharging the battery once daily the simulated BEV will not be able to satisfy the energy requirements of these high-energy driving days without using the fast charging. For Minneapolis, there are 1,971 total driving days that cannot be completely covered with one battery full-charging.

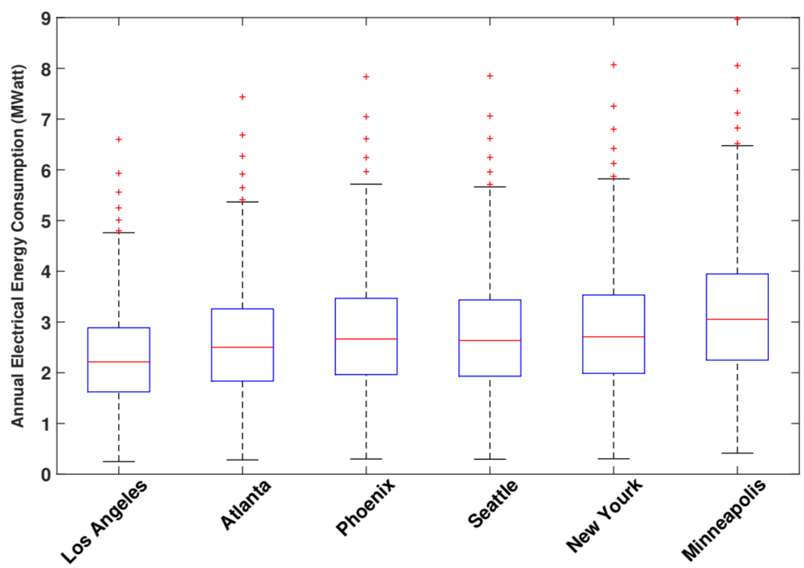


Figure 5.11. Distribution of the annual electrical energy required to cover all activities of the 376 PSRC vehicles in the six US cities.

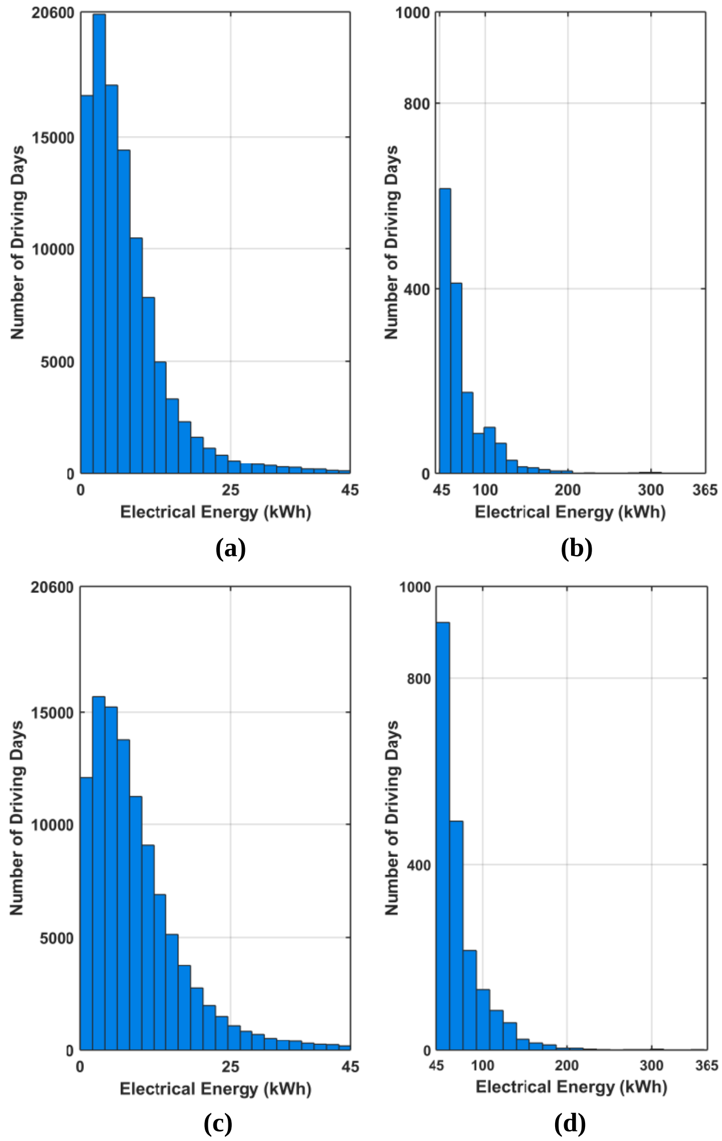


Figure 5.12. Distribution of the daily energy consumption to cover all the driving days of the 376 PSRC vehicles for two cities. a) Los Angeles 0 – 45 kWh. b) Los Angeles 45 – 365 kWh. c) Minneapolis 0 – 45 kWh. d) Minneapolis 45 - 365 kWh.

Figure 5.13 shows the distribution of the electrical energy obtained from battery charging events for the 376 PSRC vehicles in Los Angeles within the one-year period. The distribution shows that by following my proposed battery charging strategy, the battery is recharged in small amounts more frequently than in large amounts and this is what recommended by the automaker to prolong the battery life.

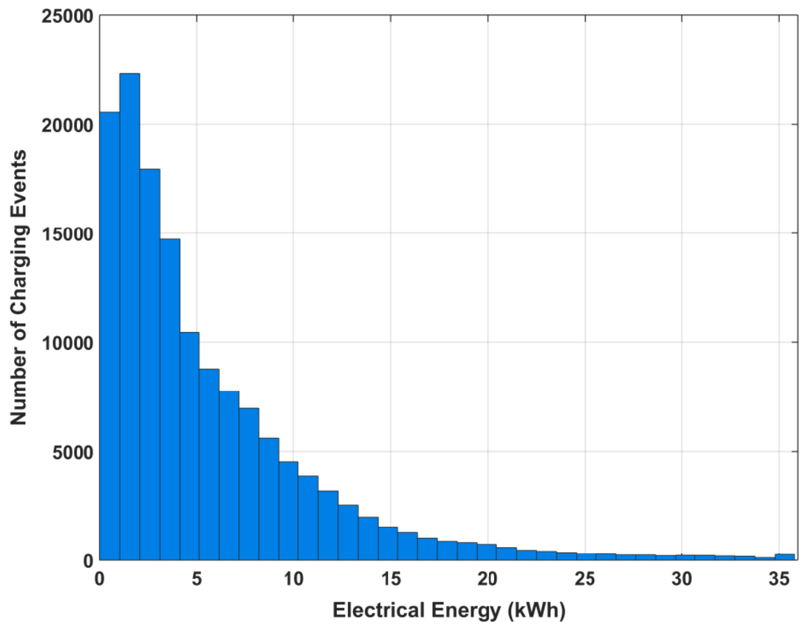


Figure 5.13. Distribution of charging energy acquired by the 376 PSRC vehicles in one year in Los Angeles.

For battery cooling during charging events, the results, such as those illustrated in Figure 5.14, show that the simulated BEV in the hot-climate cities, such as Phoenix, requires much more energy for battery cooling (energy consumed by cooling fan) during charging events than in the other cities. Figure 5.14 shows the distribution of percent of charging events that started with battery cooling to the total number of charging events for the 376 PSRC vehicles in the six cities.

In the city of Minneapolis, because of the severe cold temperatures during winter, the battery needed to be warmed by its electrical warmer in several cases to avoid being damaged. The distribution of the annual electrical energy consumed by the battery warmer in the parking events for the 376 PSRC vehicles in Minneapolis is shown in Figure 5.15.

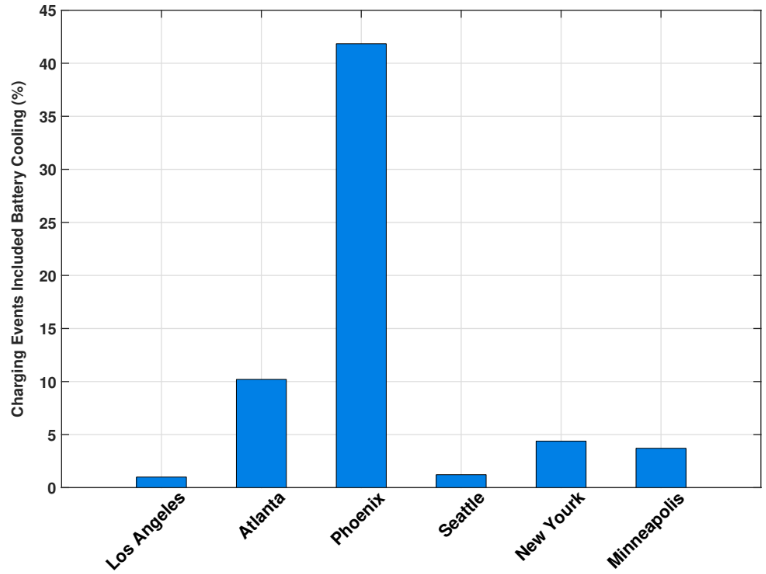


Figure 5.14. Distribution of percent of charging events that included battery cooling to the total number of charging events for the 376 PSRC vehicles in the six cities.

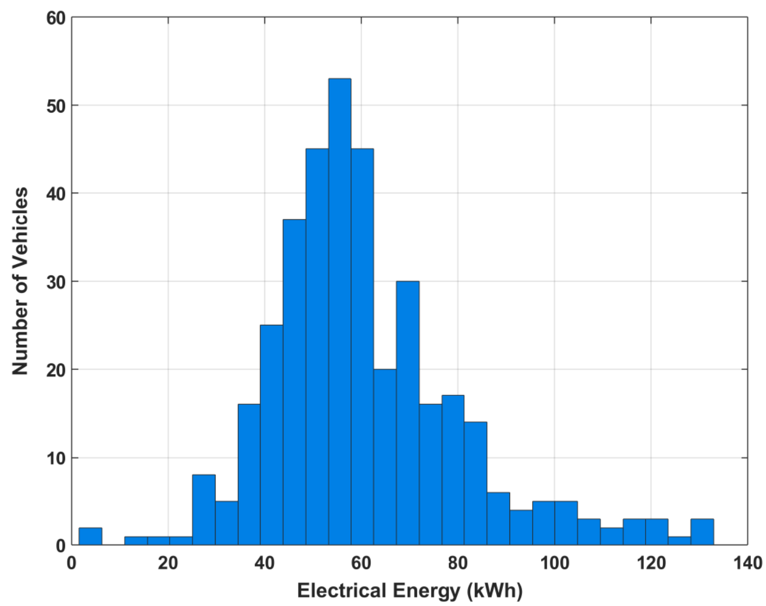


Figure 5.15. Distribution of the electrical energy consumed by battery warmer for the 376 PSRC vehicles in one year in Minneapolis.

The average vehicle consumes about 58 kWh of electrical energy for battery warming. So, to protect the battery, drivers in Minneapolis need to consider battery warming during the non-charging parking events on severely cold winter days.

To show the importance of using the real-world driving cycles in BEV performance studies, I compared the fuel economy (expressed as AC energy consumption) of the representative BEV at 72 °F ambient temperature with climate control off for the EPA City and Highway cycles, separately, to its fuel economy for the trips of the used dataset that have distance and average speed similar to the City and Highway cycles of EPA with a distance and average speed error band of ± 3%. The study in [47] provided a similar comparison, but only for the EPA Highway cycle with their representative BEV. Figure 5.16(a) shows the distribution of the energy consumption of the representative BEV for the dataset trips with distance and average speed similar to the City cycle of EPA with a distance and average speed error band of ± 3% and the fuel economy of the EPA City cycle. Figure 5.16(b) shows the speed profiles of the EPA City cycle and the cycles of the three dataset EPA-similar trips shown in Figure 5.16(a). Figure 5.17(a) shows the distribution of the energy consumption for the dataset trips with distance and average speed similar to the Highway cycle of EPA with a distance and average speed error band of ± 3% and the fuel economy of EPA Highway cycle while Figure 5.17(b) shows the speed profiles of the EPA Highway cycle and the cycles of the three dataset similar trips that shown in Figure 5.17(a).

It can be noticed from Figures 5.16 and 5.17 that the fuel economy (AC energy consumption) for the City cycle of EPA is less than the average of the fuel economy of the dataset similar-trips, but not too far while for the EPA Highway cycle, the BEV fuel economy for the EPA Highway cycle is less than the fuel economy of the 5th percentile of

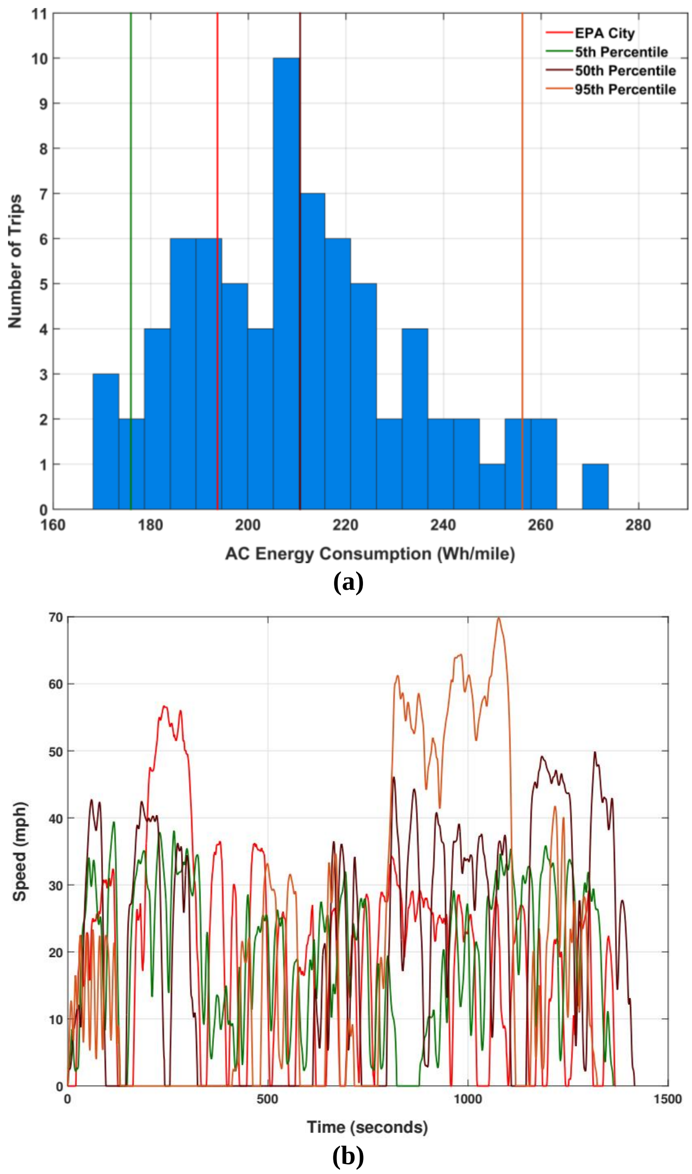
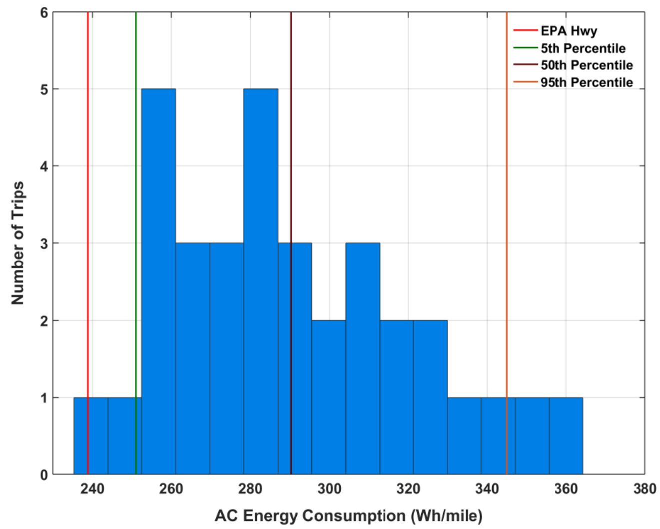
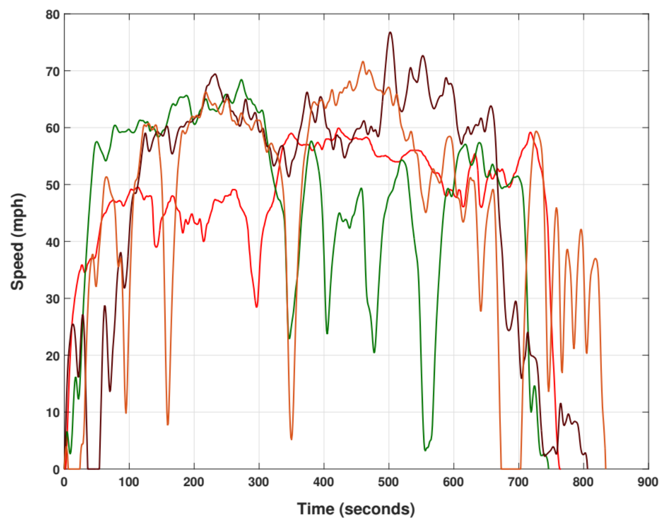


Figure 5.16. Comparison between the fuel economy of the simulated BEV for the EPA City cycle and the dataset trips with distance and average speed similar to the City cycle of EPA with a distance and average speed error band of ± 3%. a) Distribution of the AC energy consumption for the dataset trips with distance and average speed similar to the City cycle of EPA. b) Speed profiles of the EPA City cycle and the three dataset trips indicated above in Figure 5.16(a).

the dataset similar-trips. Generally, it can be noticed that the BEV consumes more energy (less MPGe) in real-world trips than it does in the testing cycles provided by EPA for both City and Highway cycles.



(a)



(b)

Figure 5.17. Comparison between the fuel economy of the simulated BEV for the EPA Highway cycle and the dataset trips with distance and average speed similar to the Highway cycle of EPA with a distance and average speed error band of ± 3%. a) Distribution of the AC energy consumption for the dataset trips with distance and average speed similar to the Highway cycle of EPA. b) Speed profiles of the EPA Highway cycle and the three dataset trips indicated above in Figure 5.17(a).

CHAPTER 6

CONCLUSION AND FUTURE DIRECTIONS

6.1 Conclusion

The PSRC and ARC datasets are complementary in terms of time resolution, traffic and environmental conditions, and variables such as distance, average speed, and duration. The two datasets were intensively analyzed and processed. The filtering and cleansing of the PSRC data significantly improved the data reliability. Combining the ARC micro-trips that were generated from the original ARC trips with the original ARC trips increased the ARC trips distance-average speed coverage and produced better matching results for the PSRC trips. I achieved high degrees of matching between the PSRC trips and the ARC trips, original and micro-trips, and 99.978% of the total PSRC dataset trips were successfully matched. The resultant dataset is a new driving cycle database in MS Access format that can be easily queried to produce diverse second-by-second realistic driving cycles, that also includes the yearly usage patterns for 382 passenger vehicle drivers. Coupled with analyzing tools such as ADVISOR, this database can be very useful in studying vehicle fuel economy, battery life, and tailpipe emissions impact due to real-world driving scenarios. More recently, NREL and other organizations has made more vehicle travel surveys available to the public. My approach can be extended and applied to these surveys as well to generate different useful datasets.

The second-by-second driving and non-driving activities of 376 vehicles of the generated trip dataset were simulated using ADVISOR™ simulation software, the 2018

Nissan Leaf as a representative BEV, and the TMY3 temperature dataset to study the performance, utilization, and range limitations of the BEV in a period of one year. The study included the simulation of climate control power, battery thermal behavior during non-driving events, and battery charging events that are only permitted at home if the driver intends to stay home for at least 30 minutes. I found significant influence of battery charging strategy, ambient temperature, and driving pattern on the performance and utilization of the simulated BEV. The simulated BEV achieved results close to EPA rates where the average fuel economy in the six cities was 112.33 MPGe and the average driving range was 148.5 miles. Public chargers are found to be still essential for the BEV to cover all the activities of driving days during long-distance trips and driving days with several trips away from home despite the increased driving range of the 2018 model. My findings can be helpful for drivers who intend to adopt BEVs as it provided an overview on the performance, range limitations, and annual energy consumption of the representative BEV through the entire year in different climates. This also may be helpful for BEV manufacturers in their design of BEVs for the selection of battery capacity and specifications of other powertrain components. The study revealed the challenges with battery warming (or cooling) that BEV drivers face in cold-climate (or hot-climate). My proposed simulation approach can be applied to other BEV types and can simulate trips from different travel survey datasets with their driving cycles.

6.2 Future Directions

To increase the reliability of the proposed approach for generating a new trip dataset and improve the efficiency of the generated dataset, some suggested steps can be carried out. One suggestion might be using driving cycles from other different GPS travel survey datasets to be matched by the PSRC trips to either generate a diverse pool of driving cycles from different geographical locations for every PSRC trip or generate multiple trip datasets from the PSRC dataset based on the geographical locations of the datasets that their second-by-second driving cycles will be used as the matches for the PSRC trips. However, this suggestion depends on the availability of travel survey datasets that include GPS data collected in a period of one week or more to better serve for the trip matching process compared to the collection period of the GPS data in the ARC dataset I used. Another suggested step is to combine other travel survey datasets that may cover reasonably large different parts of the year to generate a full year trip dataset that may include more vehicles and trips than the PSRC dataset.

For the BEV utilization and performance study, to perform more reliable and generalized study, one may use velocity profiles of deriving cycles that were made in each city of the study, if possible, to efficiently consider the effect of vehicle driving pattern. Driving cycles may differ from one city to another considering several factors that may influence them such as infra structure and vehicle speed regulations. Additionally, to improve the results of the study, I suggest to include and analyze the effect of aging on battery efficiency. My study covers the first full year of the BEV life and the influence of battery aging was not included. Moreover, as suggested for improving the trip dataset generated in the first part of this dissertation, publicly available travel survey datasets may be more deeply explored and such a full year dataset that can be generated by combining trips made by vehicles from different travel survey datasets that were run in different geographical locations may serve more efficiently for the BEV simulation study.

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ABSTRACT

DEVELOPING A REAL-WORLD VEHICLE TRIP DATASET THROUGH PUBLIC TRAVEL SURVEYS AND APPLYING IT TO BATTERY ELECTRIC VEHICLE PERFORMANCE STUDY

by

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May 2020

Advisor: Prof. Hao Ying

Major: Electrical Engineering

Degree: Doctor of Philosophy

Real-world second-by-second vehicle driving cycle data is very important for research and development of the traditional fuel-powered vehicles, the emerging electric vehicles, and the hybrid vehicles. A project solely dedicated to generating such information would be extremely costly and time-consuming. Alternatively, we introduce a method to develop such a database by utilizing two publicly available passenger vehicle travel surveys; the 2004-2006 Puget Sound Regional Commission (PSRC) Travel Survey and the 2011 Atlanta Regional Commission (ARC) Travel Survey. The two surveys complement each other – the former is in low time resolution but covers vehicle driving and non-driving operation for over one year whereas the latter is in high time resolution but represents only one-week long driving operation. After analyzing the PSRC survey, we chose 382 vehicles, each of which continuously operated for one year, and then match their trips to all the ARC trips after generating ARC sub-trips from the original ARC trips. The matching is carried out based on trip distance first, then on average speed, and finally on duration. Of the total

509,158 trips made by the 382 PSRC vehicles, 496,276 trips (97.47%) are successfully matched by single original ARC trips. The remaining trips are matched by either ARC sub-trips or combined ARC trips. The resulting high-resolution year-long database can be used by drive cycle analysis tools such as the advanced vehicle simulator ADVISOR™ to investigate fuel economy, battery life, and vehicle emissions under various driving and climate conditions. Our approach can be employed to produce other realistic databases from other publicly available vehicle travel surveys.

Utility and performance of Battery Electric Vehicles (BEVs) are affected by important factors such as battery recharging strategy, ambient temperature, and driving pattern. None of the studies in the literature covers the performance or utility of BEV for a full year using second-by-second vehicle driving and non-driving activities. Furthermore, most used recharging strategies do not relate to trip actual destination. I study these same factors but employ year-long, second-by-second activities of 376 passenger vehicles from the dataset I generated in the first part of this dissertation along with their trip destinations. I use ADVISOR™ software with the 2018 Nissan Leaf as a representative BEV. Los Angeles, Atlanta, Phoenix, Seattle, New York, and Minneapolis are chosen to create diverse ambient temperature profiles from the Typical Meteorological temperature dataset and all the 376 vehicles are assumed to operate in each of these cities. The battery is recharged with a Level-2 charger immediately after driver reaches home if the BEV will not be used for at least 30 minutes. Charging may continue until next trip starts. Our simulation shows that this recharging strategy can cover all activities of 15% of the vehicles. It Also covers 94.82% of the driving days in the year performed by an average vehicle in the remaining vehicle pool. The average fuel economy of the simulated BEV in the six cities is 112.33 MPGe while the average range is 148.5 miles. The BEV requires, on average, 2.31 MW of electrical energy to cover year-long activities of a vehicle in a mild-climate city (i.e. Los Angeles) while in a cold-climate city (i.e. Minneapolis) the average increases to 3.18 MW. Our findings reveal BEV performance under more realistic driving and non-driving conditions. Such study can be extended and employed to explore and analyze other types of BEVs.

AUTOBIOGRAPHICAL STATEMENT

NIZAR ALI KHEMRI is from Mesallata, Libya and was born in Khums, Libya. He received his National Diploma (equivalent to a high school diploma) in Electronic Maintenance in 1997 from Petroleum Training and Qualifying Institute, Tripoli, Libya. In 2006, he received his Bachelor of Science degree in Computer Engineering from University of Tripoli, Tripoli, Libya. He received a Master of Science degree in 2012 in Electrical and Computer Engineering from Oklahoma State University, Stillwater, Oklahoma, US.